



# **NAVAL POSTGRADUATE SCHOOL**

**MONTEREY, CALIFORNIA**

## **THESIS**

**IMPROVING MARINE CORPS TOTAL LIFE CYCLE  
MANAGEMENT BY CONNECTING COLLECTED DATA  
AND SIMULATION**

by

Shawn M. Phillips

June 2009

Thesis Advisor:

Thomas W. Lucas

Second Reader:

Stephen H. Mount

**Approved for public release; distribution is unlimited**

THIS PAGE INTENTIONALLY LEFT BLANK

<b>REPORT DOCUMENTATION PAGE</b>			<i>Form Approved OMB No. 0704-0188</i>	
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.				
<b>1. AGENCY USE ONLY (Leave blank)</b>		<b>2. REPORT DATE</b> June 2009	<b>3. REPORT TYPE AND DATES COVERED</b> Master's Thesis	
<b>4. TITLE AND SUBTITLE</b> Improving Marine Corps Total Life Cycle Management by Connecting Collected Data and Simulation			<b>5. FUNDING NUMBERS</b>	
<b>6. AUTHOR(S)</b> Shawn M. Phillips				
<b>7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)</b> Naval Postgraduate School Monterey, CA 93943-5000			<b>8. PERFORMING ORGANIZATION REPORT NUMBER</b>	
<b>9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)</b> Marine Corps Installations and Logistics Washington, D.C. 20380-1775			<b>10. SPONSORING/MONITORING AGENCY REPORT NUMBER</b>	
<b>11. SUPPLEMENTARY NOTES</b> The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.				
<b>12a. DISTRIBUTION / AVAILABILITY STATEMENT</b> Approved for public release; distribution is unlimited			<b>12b. DISTRIBUTION CODE</b> A	
<b>13. ABSTRACT (maximum 200 words)</b> <p>Marine Corps Total Life Cycle Management (TLCM) is critical in meeting requirements established in Department of Defense Directive 4151.18, notably, "optimizing ... concepts to deliver efficient and effective performance to the operating forces." Modeling and simulation (M&amp;S) creates an opportunity to explore improvement opportunities before costly decisions are implemented. Unfortunately, applying M&amp;S to TLCM efforts has been hampered in the past by an inefficient, error prone process of moving gathered data to an M&amp;S platform.</p> <p>This research uses Visual Basic for Applications to link two Marine Corps TLCM tools: the Systems Operational Effectiveness Decision Support Tool (SOE DST) and the Total Life Cycle Management Assessment Tool (TLCM-AT). The Bridging Operational Logistics Tool (B-OLT) is created to allow TLCM-AT models to be built automatically, using existing SOE DST data and limited subject matter expert inputs.</p> <p>The B-OLT built models are assessed, exercised with state-of-the-art design of experiments and used to predict future events.</p> <p>The research shows a link between data currently collected and simulation allows for quantitative analysis. This analysis explores the Marine Corps' data collection and summary techniques, and their application to modeling, demonstrating how B-OLT can be used to aid in future analytical efforts.</p>				
<b>14. SUBJECT TERMS</b> Simulation, Design of Experiments, Life Cycle Management, VBA, Modeling			<b>15. NUMBER OF PAGES</b> 81	
			<b>16. PRICE CODE</b>	
<b>17. SECURITY CLASSIFICATION OF REPORT</b> Unclassified	<b>18. SECURITY CLASSIFICATION OF THIS PAGE</b> Unclassified	<b>19. SECURITY CLASSIFICATION OF ABSTRACT</b> Unclassified	<b>20. LIMITATION OF ABSTRACT</b> UU	

THIS PAGE INTENTIONALLY LEFT BLANK

**Approved for public release; distribution is unlimited**

**IMPROVING MARINE CORPS TOTAL LIFE CYCLE MANAGEMENT  
BY CONNECTING COLLECTED DATA AND SIMULATION**

Shawn M. Phillips  
Captain, United States Marine Corps  
B.A., The Citadel, 2000

Submitted in partial fulfillment of the  
requirements for the degree of

**MASTER OF SCIENCE IN OPERATIONS RESEARCH**

from the

**NAVAL POSTGRADUATE SCHOOL  
June 2009**

Author: Shawn M. Phillips

Approved by: Thomas W. Lucas  
Thesis Advisor

Stephen H. Mount  
Second Reader

Robert F. Dell  
Chairman, Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

## **ABSTRACT**

Marine Corps Total Life Cycle Management (TLCM) is critical in meeting requirements established in Department of Defense Directive 4151.18, notably, “optimizing ... concepts to deliver efficient and effective performance to the operating forces.” Modeling and simulation (M&S) creates an opportunity to explore improvement opportunities before costly decisions are implemented. Unfortunately, applying M&S to TLCM efforts has been hampered in the past by an inefficient, error prone process of moving gathered data to an M&S platform.

This research uses Visual Basic for Applications to link two Marine Corps TLCM tools: the Systems Operational Effectiveness Decision Support Tool (SOE DST) and the Total Life Cycle Management Assessment Tool (TLCM-AT). The Bridging Operational Logistics Tool (B-OLT) is created to allow TLCM-AT models to be built automatically, using existing SOE DST data and limited subject matter expert inputs.

The B-OLT built models are assessed, exercised with state-of-the-art design of experiments and used to predict future events.

The research shows a link between data currently collected and simulation allows for quantitative analysis. This analysis explores the Marine Corps’ data collection and summary techniques, and their application to modeling, demonstrating how B-OLT can be used to aid in future analytical efforts.

THIS PAGE INTENTIONALLY LEFT BLANK



## TABLE OF CONTENTS

<b>I.</b>	<b>MARINE CORPS MAINTENANCE IS COMMITTED TO SUPPORTING THE WARFIGHTER.....</b>	<b>1</b>
<b>A.</b>	<b>TLCM PROMOTES ASSET AVAILABILITY.....</b>	<b>1</b>
<b>B.</b>	<b>RELATED ELEMENTS CENTRAL TO TLCM.....</b>	<b>1</b>
	1. Collecting and Summarizing Data .....	3
	2. Developing Logical Predictions Pertaining to the Impact of Policy Decisions .....	3
<b>C.</b>	<b>SYSTEM OPERATIONAL EFFECTIVENESS DECISION SUPPORT TOOL (SOE DST) AND TLCM ASSESSMENT TOOL (TLCM-AT) FOR TLCM WITHIN THE MARINE CORPS .....</b>	<b>4</b>
	1. SOE DST.....	4
	2. TLCM-AT.....	5
<b>D.</b>	<b>JOINT EMPLOYMENT OF SOE DST AND TLCM-AT.....</b>	<b>5</b>
<b>E.</b>	<b>PROBLEM FORMULATION AND RESEARCH DEVELOPMENT .....</b>	<b>6</b>
	1. Problem Formulation .....	6
	2. Link Automation.....	8
	3. Assess the Goodness of the Automated Model-Build Process.....	8
	4. Initial Examination of Predictive Capacity .....	8
	5. Test Sensitivities by Varying Input Factors .....	9
<b>F.</b>	<b>BENEFITS OF AUTOMATING THE MODEL-BUILD PROCESS.....</b>	<b>9</b>
<b>G.</b>	<b>THESIS ROAD MAP .....</b>	<b>9</b>
<b>II.</b>	<b>SOE DST FOR DATA SYNTHESIS AND AWARENESS.....</b>	<b>11</b>
<b>A.</b>	<b>PURPOSE OF SOE WITHIN LIFE CYCLE MANAGEMENT .....</b>	<b>11</b>
<b>B.</b>	<b>SOE PROVIDES A PICTURE OF CURRENT POSTURE.....</b>	<b>12</b>
<b>C.</b>	<b>SOE DST HISTORICAL RECORD OF SYSTEMS MAINTENANCE ..</b>	<b>13</b>
	1. Display and Synthesis of Raw Data.....	13
	2. Failure Rates and the Stochastic Modeling Process .....	14
<b>III.</b>	<b>TLCM-AT: A STOCHASTIC MODELING PLATFORM DESIGNED TO USE CURRENT DATA FOR QUANTITATIVE PREDICTIONS .....</b>	<b>17</b>
<b>A.</b>	<b>TLCM-AT: A MODEL PLATFORM, NOT A MODEL.....</b>	<b>17</b>
<b>B.</b>	<b>TLCM-AT: INPUT CONSISTENCY CONCERNS .....</b>	<b>19</b>
	1. SME Inputs are Often Used, but are not Universally Consistent.....	19
	2. Historical Data Inputs .....	20
<b>C.</b>	<b>TLCM-AT CAN IMPROVE MAINTENANCE PROCESS UNDERSTANDING .....</b>	<b>21</b>
<b>IV.</b>	<b>B-OLT MOVES SOE DATA INTO THE TLCM-AT PLATFORM.....</b>	<b>23</b>
<b>A.</b>	<b>SOE DATA CONVERSION TO TLCM-AT .....</b>	<b>23</b>
	1. Building the System Module within TLCM-AT .....	23
	2. Building the Operations Module within TLCM-AT.....	25
	3. Building the Maintenance Module within TLCM-AT .....	26

4.	Building the Sustainment Module within TLCM-AT .....	30
B.	B-OLT CODING IN VISUAL BASIC FOR APPLICATIONS (VBA) ....	30
V.	B-OLT-DRIVEN MODELS ASSESSMENT .....	33
A.	VERIFICATION/ASSESSMENT:        MODELED    FAILURES COMPARED TO DATA HISTORY .....	33
B.	FURTHER EXPLORATION OF ALL REGIONAL ACTIVITIES CODES MODEL.....	37
C.	STEPS TOWARD VALIDATION:  PREDICTIONS MADE BY VERIFIED MODELS.....	38
1.	Known Changes Key in Testing Prediction Capability .....	38
2.	The Model Demonstrated an Increase in Failures Based on Known Expected Operational Tempo Changes .....	39
VI.	MODELS' SENSITIVITY TO INITIAL FACTORS .....	43
A.	NEARLY ORTHOGONAL LATIN HYPERCUBE (NOLH) DESIGN EXPLANATION.....	43
B.	GENERAL DOE FOR SENSITIVITY ANALYSIS FOR FACTORS USED IN THE MODEL-BUILD.....	43
C.	SENSITIVITY RESULTS.....	44
D.	FACTORS OF INTEREST BASED ON SENSITIVITY ANALYSIS .....	48
VII.	INSIGHTS GAINED USEFUL TO FUTURE TLCM EFFORTS.....	51
A.	VERIFICATION OF THE AUTOMATED-BUILD PROCESS.....	51
B.	ASSESSMENT OF B-OLT-GENERATED MODELS .....	51
C.	INITIAL FACTORS OF INTEREST IDENTIFIED USING SOE DST AND TLCM-AT .....	52
D.	SIGNIFICANCE OF AUTOMATED-BUILD PROCESS.....	52
1.	Time Involved in Manually Building TLCM-AT Models is Considerable.....	52
2.	Opportunity for Use by All PMs for All TAMCNs.....	52
3.	Opportunity to Apply DOE to Policy Decisions.....	53
4.	Opportunity to Work toward Model Validation .....	53
E.	FUTURE WORK OPPORTUNITIES.....	53
1.	Exploration of Predictive Factors for TLCM-AT Airframe Models .....	53
2.	Cost Benefit Analysis for Automating Data Collection .....	54
3.	Further Development of B-OLT Using Other Data Sources and Model Platforms.....	54
4.	Application of the Model-Building Process to Promote its Validation of Maintenance Models .....	54
	LIST OF REFERENCES .....	57
	INITIAL DISTRIBUTION LIST .....	59

## LIST OF FIGURES

Figure 1.	The SOE to TLCM-AT link developed by B-OLT. ....	xvii
Figure 2.	The incorporation of modeling and simulation in the existing TLCM process.....	3
Figure 3.	System Operational Effectiveness data-gathering structure. ....	12
Figure 4.	The TLCM-AT continuous-loop model (From: ATLAST Technical Reference Manual, 1992-2005). The outer green boxes represent model modules. Each inner box is an external factor that may effect any of the outer modules. The inner blue terms represent user inputs and the outer black terms are model outputs. This is best viewed in color. ....	18
Figure 5.	The work breakdown structure possible in TLCM-AT, as compared to the limited structure in an SOE DST-driven model.....	24
Figure 6.	The base structure possible in TLCM-AT, as compared to the limited base structure in an SOE DST-driven model. ....	25
Figure 7.	The maintenance flow module in TLCM-AT. This is best viewed in color. ....	28
Figure 8.	The link developed with B-OLT between data and simulation. ....	31
Figure 9.	The distribution of proportion difference between the actual failures and modeled failures.....	34
Figure 10.	Proportion difference on adjusted vehicle population actual failures v. modeled failures.....	35
Figure 11.	Distribution of Model Failures–SOE DST failures across TAMCNs in the Marine Corps total population. The model is overestimating failure events in general.....	36
Figure 12.	The correlations between URR, Part Count, and Difference across all TAMCNs.....	36
Figure 13.	Parameter estimates for all RACs data for all TAMCNs.....	37
Figure 14.	The correlation coefficients of the number of part failures, URR, and the difference between model and reality. The prediction exercise shows promise and the correlations suggest where improvement can be made. ....	40
Figure 15.	The results of provisioning with predictive model. The columns represent one, two, or three standard deviations above the modeled requirement minus the actual requirements in 2003. ....	40
Figure 16.	The NOLH DOE produced for the D0187.....	45
Figure 17.	The correlations in the NOLH DOE performed on the D0187 variant. The positive correlation between RMSD and RC indicate that an increase in RC will result in a larger overall change in the model’s ability to back validate well. ....	46
Figure 18.	The correlation coefficients for the D1001 (left) and D1002 (right) variants.....	47
Figure 19.	Correlation coefficients for all variants together. ....	47
Figure 20.	The parameter estimates for D0187 on 16 design points. The R-Squared for the model is 95%, with an adjusted of 92%. The model fits well.....	49

Figure 21. The parameter estimates for D0187 on 32 design points across 174 parts.  
The R-Squared for the model is 75% with and adjusted of 75%.....49

## LIST OF TABLES

Table 1.	Inspection time, in hours, assumptions applied to an SOE DST-driven model.....	29
Table 2.	Tear time assumptions applied to an SOE DST-driven model. ....	29
Table 3.	NOLH DOE factors that are common between all TAMCNs. ....	43
Table 4.	Design of experiments with the addition of the Parts Count column. The Parts Count is the number of parts modeled per vehicle. ....	48

THIS PAGE INTENTIONALLY LEFT BLANK

## **LIST OF SYMBOLS, ACRONYMS, AND ABBREVIATIONS**

AM	Annual Miles
B-OLT	Bridging Operational Logistics Tool
CASC	Capabilities Assessment Support Center
CTC	Concurrent Technologies Corporation
DoD	Department of Defense
DOE	Design of Experiments
ERO	Equipment Repair Order
HMMWV	High Mobility Multipurpose Wheeled Vehicle
IDFW	International Data Farming Workshop
I MEF	First Marine Expeditionary Force
JLTV	Joint Light Tactical Vehicle
LRT	Logistics Response Time
LRU	Line Replaceable Unit
MAC	Maintenance Allocation Chart
MCSC	Marine Corps Systems Command
MOE	Measure of Effectiveness
MPH	Miles Per Hour
M&S	Modeling and Simulation
NOLH	Nearly Orthogonal Latin Hypercube
NRTS	Not Repairable This Station
NSN	National Stock Number
PEI	Principle End Item
PM	Program Manager
ProbCon	Probability of Condemnation
RAC	Regional Activity Codes
RC	Ratio Change
RMSD	Root Mean Square Difference
SD	Standard Deviation

SL	Stock List
SME	Subject Matter Expert
SMR	Source, Maintenance, and Recoverability
SOE	Systems Operational Effectiveness
SOE DST	Systems Operational Effectiveness Decision Support Tool
TAMCN	Table of Authorize Materiel Control Number
TLCM	Total Life Cycle Management
TLCM-AT	Total Life Cycle Management Assessment Tool
URR	Unscheduled Removal Rate
VAMOSC	Visibility & Management of Operation & Support Cost
VBA	Visual Basic for Applications
VC	Vehicle Count
WS	Weapons System



## EXECUTIVE SUMMARY

Marine Corps Total Life Cycle Management (TLCM) is critical in meeting the requirements established in Department of Defense Directive 4151.18, notably, “optimizing . . . operating concepts to deliver efficient and effective performance to the operating forces” (Wolfowitz, 2004). Modeling and simulation (M&S) creates an opportunity to explore improvement opportunities before costly decisions are implemented. Applying M&S to TLCM efforts has been hampered in the past by an inefficient, error-prone, and laborious process of moving gathered data to an M&S platform. This research applies Visual Basic for Applications code to the problem of migrating data gathered and summarized to a modeling environment. These models are then assessed, used as a predictive tool, and their sensitivities to input factors explored. Through automation, M&S can more readily be used to explore program improvements, improve provisioning efforts, and define budget requirements to support maintenance.

TLCM is a complicated process. The most powerful tools of the TLCM facilitator are good data and simulation. The data collected provide information about the end item. Simulation provides a way to test changes to the system before costs are incurred. The use of data collected in simulation, in a process-oriented way, makes M&S accessible, allows for easy implementation of design of experiments (DOE), and makes validation possible.

To be functional, the process must be easily executed and understood. The user should also have a reason to use the process. This research offers an approach to meeting this process requirement by using the following questions as a guide:

- Can the development of Total Life Cycle Management Analysis Tool (TLCM-AT) models be aided through automation?
- What gaps are there between data summarized in the Systems Operational Effectiveness Decision Support Tool and data required in TLCM-AT?
- Once a TLCM-AT model is built, how well does the model assess against reality; and what factors are most relevant?
- Given an assessed model and known fluctuations in operational tempo or vehicle population, can the model predict changes in parts failure events?

The Marine Corps has contracted two independent TLMC tools: The Systems Operational Effectiveness Decision Support Tool (SOE DST) and TLMC-AT. These two TLMC tools are not connected, causing their full potential to go unrealized. SOE DST collects inputs from over 12 maintenance and supply user interfaces. These inputs pertain to critical end items used throughout the Marine Corps. SOE DST reports historical facts pertaining to these end items; it is not designed to act as a predictive tool. TLMC-AT has the ability to make predictions based on projected operational tempo, distributions of failure rates, and logistics response times, but requires real-time data in order to produce accurate and relevant output. While SOE DST contains information necessary to populate TLMC-AT, there is no established interface between the two systems.

It is essential to have a tool that can link SOE DST and TLMC-AT. The link should be automated to ensure tested accuracy of the process. The result of the link is an opportunity to rapidly employ a predictive model with data that is readily available to program managers.

This research challenges old constructs of TLMC-AT models built by modeling professionals from Clockwork Solutions using multiple sources of inputs, to include SOE DST. The Bridging Operational Logistics Tool (B-OLT) was built to automate the model-build process. While licenses are available to the Marine Corps, the model-build process is currently too complicated to be functionally practical. Prior to B-OLT, it took a trained TLMC-AT user approximately three days to build a rudimentary model strictly from SOE DST with limited subject matter expert data. B-OLT uses SOE DST data to build, run, and extract output from a powerful, closed-loop, stochastic model in TLMC-AT in less than 10 minutes. The automation demonstrates the ability to put M&S in the hands of program managers in a user-friendly way. Figure 1 demonstrates this process.

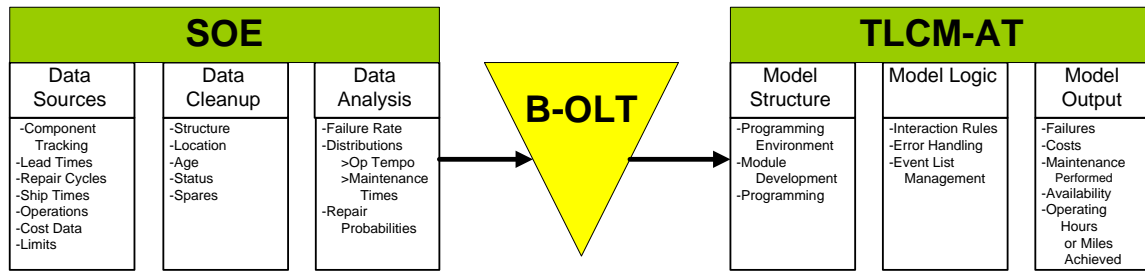


Figure 1. The SOE to TLCM-AT link developed by B-OLT.

The automation itself saves time, makes modeling accessible to all Table of Authorize Materiel Control Numbers reported by SOE DST, produces results from data that can be validated, and allows DOE to be applied to gain insight for policy decision making.

Through the process of assessment, ways to enhance SOE DST are discovered. The B-OLT-built model reported within 10% of the same failures experienced in reality. The proximity to reality makes the models practical to use in future ‘what if’ analysis. In the course of this research, opportunities to improve SOE DST for use as input into M&S platforms were discovered. There are factors missing from SOE DST that are necessary for TLCM M&S: the average miles per hour and miles driven, maintenance and supply times, indenture structure and the vehicle counts used to compute failure rates. Indentured structure will allow for a more robust series of models by reducing the amount of memory taken by the simulation. The remaining factors directly affect the outputs from the model.

With B-OLT, multiple models can be built and executed in sequence, allowing a DOE application to determine input factors of interest. The measures of effectiveness can be chosen from any number of outputs, such as cost or performance. This research used modeled versus real failures as the measure of effectiveness. Through DOE, it was discovered that the failure rate and vehicle counts are the most important consideration in terms of data inputs. Knowing this gives focus of effort when considering where to improve data collection in the future.

Once the B-OLT model-building process is assessed, it is used to predict failures. An automated model built from 2002 data is used to predict 2003 requirements. The First

Marine Expeditionary Unit is used as the test bed. From 2002 to 2003, the unit's operational tempo and vehicle populations increased in response to mission requirements. Using the future increase in operational tempo and population, coupled with 2002 SOE DST data only, models were built and run. The models were able to accurately predict future requirements. If the model had been used to build a provisioning package, the unit would have enjoyed favorable results. Specifically, the results show that going one standard deviation more than the model's prediction would have resulted in being short on only 17 of 297 parts during the one-year provisioning period.

There are important lessons learned that must be addressed to improve the overall TLCM data gathering to simulation process; however, this research provides a demonstrated capability to move from data that is already collected and summarized to a predictive model in an automated manner. By automating many human-in-the-loop activities, variability and bias is removed from the models created. Further, the process, and its associated data, can be validated over time. This automation can lead to validation of the model-build process and put modeling in the hands of PMs to assist in policy decisions.

## ACKNOWLEDGMENTS

The research represented in this thesis is a collaborative effort. The work began 38 years ago, when my parents gave me not only life, but a solid foundation. It has continued only with the unyielding support of my wife and children. Along the way, many have influenced my growth and there is no way to acknowledge everyone.

For the life they gave and the lessons they taught, I must thank my parents. Without Lloyd and Juanita Phillips' love, support, and compassion, I would not be half the man I am today. Mom and Dad, thank you.

You can do good things by your actions. You may have great accomplishments with proper support. I am forever grateful to my lovely wife, Lisa. Lisa, without you, I have no reason to achieve and limited capacity to do so. I will forever be in your debt for the sacrifices you have made. Truthfully, I am grateful for your love, support, and ability to put up with a guy like me. Thank you. I love you.

Children are fortunate to have good parents; parents are blessed to have good kids. Ashley and Tiffani, there is no father around with more reason to be proud of their children than me. You have been patient with my work and eagerly strive toward your own accomplishments. I have the luxury of knowing my children will succeed, no matter the obstacles. To my children, thank you. I love you.

Finally, I must thank the professors of the Naval Postgraduate School from whom I have had the pleasure of taking instruction. Each has had the pleasure of my time during office hours. More importantly, each, without reserve, has been eager to help. I could not have done it without their help.

This research is not simply hours of my own work; it is years of support, mentoring, and patience afforded to me by people I am honored to have been fortunate enough to know. Thank you.

THIS PAGE INTENTIONALLY LEFT BLANK

## **I. MARINE CORPS MAINTENANCE IS COMMITTED TO SUPPORTING THE WARFIGHTER**

Marine Corps Total Life Cycle Management (TLCM) is critical in meeting the requirements established in Department of Defense (DoD) Directive 4151.18, notably, “optimizing . . . operating concepts to deliver efficient and effective performance to the operating forces” (Wolfowitz, 2004). Modeling and simulation (M&S) creates an opportunity to explore improvement opportunities. Applying M&S to TLCM efforts has been hampered in the past by an inefficient, error-prone, and laborious process of moving gathered data to an M&S platform.

TLCM is a complicated process. The tools of the TLCM facilitator are data collected on the assets that are being managed and simulation. The data collected provide information about the weapon system or end item. Simulation provides a way to test changes to the system before costs are incurred. The use of data collected in simulation, in a systematic way, allows not only for end item improvements, but also identifies important data to improve models. This chapter reviews the Marine Corps’ TLCM assets and the focus of the research.

### **A. TLCM PROMOTES ASSET AVAILABILITY**

The ability of the Marine Corps to accomplish its mission is reliant on personnel and equipment readiness. TLCM is the process by which program managers (PMs) assess a principal end item throughout its lifetime and ensure its availability. Policy, procedural, and performance upgrades may be required to ensure the most efficient use of a piece of equipment. Through M&S, the guesswork may be taken out of policy and management decisions. This research bridges a gap between summarized data and a modeling platform, to allow for validation of the model build process and improved TLCM through the use of simulation.

### **B. RELATED ELEMENTS CENTRAL TO TLCM**

According to Marine Corps Order (MCO) 4000.57, TLCM is the “formal process to identify, analyze, and implement synergistic ‘cradle to grave’ solutions that optimize

the acquisition/logistics chain across the Marine Corps in support of operating forces” (Kelly, 2005). Included in TLCM is prognostics- and performance-based logistics. To improve the maintenance process and TLCM in general, data must be collected and analyzed, and action, perhaps in the form of policy, taken to improve those areas determined to be in need of change.

A key to success is the ability to collect and summarize data, and then use this data to simulate possible realities. Once such a model is established, factors may be adjusted to reflect potential management decisions or policy changes aimed at improving performance, increasing availability, or lowering the cost of maintenance. The Marine Corps has contracted to develop a data summarizing tool aimed at assessing the overall performance of equipment. Additionally, a modeling platform has been purchased to build predictive models that provide analysis using Monte Carlo-based simulation.

TLCM is a process. Initially, a way of doing business is established. As the end item and its supply and maintenance systems are executed, problems resulting from unforeseen circumstances are identified. With the use of M&S, possible system improvements can be tested prior to implementation. In the case of TLCM, there are systems/processes already defined. To effectively incorporate modeling, a current TLCM cycle must be acknowledged and applied within the model. Figure 2 shows how modeling and simulation can be incorporated in the existing TLCM process.



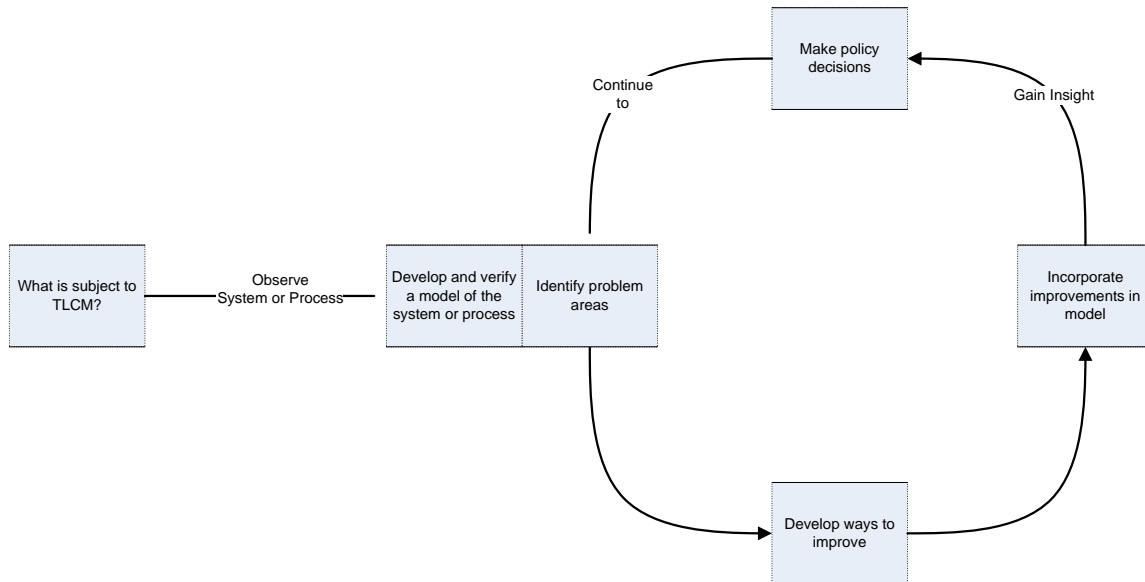


Figure 2. The incorporation of modeling and simulation in the existing TLCM process.

### 1. Collecting and Summarizing Data

To affect TLCM, the Marine Corps must collect data and articulate it in some usable format. The collection and summarizing of data allows the system's operational effectiveness to be reported, given its current and previous environment. Effectiveness here is a combination of the system's availability, reliability, and maintenance operations costs. Environmental factors may include operational tempo as well as supply and maintenance systems dynamics. Examining how the system performs, given the dynamic environment in which the system is running, allows the analyst to determine failure rates, averages of shipping times, maintenance evolutions, and other factors that affect the system's operational availability.

### 2. Developing Logical Predictions Pertaining to the Impact of Policy Decisions

The effort of developing a system's operational effectiveness gives the analyst an opportunity to collect data that can be applied to M&S efforts. With a verified and possibly validated model, developed policy decisions may be exercised in a simulated environment to determine their overall impact on defined measures of effectiveness.

Through simulation, the data collected directly impacts possible futures. Measures of effectiveness can span from availability of the end item, based on operational tempo change, to the impact of component upgrades. The benefit gained from building verified and/or validated models is the ability to quantify the benefits of program changes to make more informed decisions.

### **C. SYSTEM OPERATIONAL EFFECTIVENESS DECISION SUPPORT TOOL (SOE DST) AND TLCM ASSESSMENT TOOL (TLCM-AT) FOR TLCM WITHIN THE MARINE CORPS**

Recognizing the importance of TLCM in support of the warfighter, the Marine Corps is committed to the development of TLCM tools and processes. The baseline requirement is data collection, followed by model development.

#### **1. SOE DST**

Marine Corps Systems Command (MCSC) has contracted to develop the Web-based SOE DST as a way to monitor and identify areas of concern for maintenance and supply issues (Alionscience, 2005). The SOE DST summarizes historical data to evaluate performance and develop an understanding of possible future requirements. Through observation, historical maintenance issues may shed light on what causes a principal end item (PEI) to be in a nonavailable state. Perhaps more importantly, SOE DST produces like data for all PEI's by applying algorithms to information that is gathered from a myriad of sources. This data, therefore, is universal for select table of authorized materiel control numbers (TAMCNs). The use of the data in an M&S environment may then be validated across TAMCNs.

This Web-based application provides a logical source for data to be used in simulation efforts. A model must be verified and, eventually, may be validated. To reach a point where validation is possible, the result produced by the model must be measured against reality. When validating a model, its data must also be validated. To reduce variability between models and to permit validation, the source of inputs should be standardized. The SOE DST produces standardized data. Further, the use of the SOE DST allows the model-build process to be reusable across equipment types.

## **2. TLCM-AT**

MCSC has established a contract with the company Clockwork Solutions and has procured TLCM-AT as a closed-loop simulation model (Clockwork Solutions, Inc, 2007). The model is built by populating 41 separate Access database tables. The predictive capacity of the model is directly related to the inputs.

TLCM-AT uses a variety of input data and provides an equal amount of outputs at simulation end. These input tables represent base and supply structures, starting status of equipment, and maintenance factors. The simulation takes user inputs and builds a fleet of vehicles, based on the performance and engineering specifications of PEIs. With these inputs, TLCM-AT logic operates the modeled equipment as specified, subject to defined failure rates and supply/maintenance conditions. Through the execution of the model, multiple results are gathered and summarized as output.

Key outputs from TLCM-AT are availability, achieved operating hours, time awaiting maintenance or parts, number of tasks performed, number of parts condemned/requested, and life cycle costs. These metrics are typical questions posed during the maintenance process evaluation and are helpful when conducting TLCM. The simulation allows changes in processes or procedures to be evaluated prior to implementation. While it is not appropriate to take the results as the absolute solution, the key insights derived do well as a tool to help decision makers evaluate potential policy decisions.

### **D. JOINT EMPLOYMENT OF SOE DST AND TLCM-AT**

The full potential of SOE DST and TLCM-AT requires their joint employment. SOE DST collects inputs from a myriad of sources and systems used throughout the Marine Corps' maintenance and supply communities to report historical facts. SOE DST is not designed to act as a predictive tool. TLCM-AT has the ability to make predictions based on projected operational tempo, distributions of failure rates, and repair times, but requires current data in order to produce accurate and relevant output. While one system contains information necessary to populate the other, there is no established interface between the two systems.

In creating models using historical data that is systematically gathered and synthesized, the model-build process can be validated and reused across equipment platforms. With a clear link between data and model, there is a reduction in variability as a result of subject matter expert (SME) opinion. Additionally, all modelers will have access to the same data. As a result, the quality of the data can begin to be measured.

It is essential to have a tool that can link SOE DST and TLCM-AT. The result of the link is an opportunity to rapidly employ a predictive model with data that is readily available to PMs. If this model-build process is validated, it may be used to guide the decision-making processes pertaining to new platform purchases or upgrades, potential policy changes, and the potential impact of increased operational tempo. If the model-build process cannot be validated, it will serve to demonstrate gaps between the data collected and the predictive models the Marine Corps would like to employ. Regardless of how accurate the simulation is, it can potentially provide useful insight to aid decision makers.

## **E. PROBLEM FORMULATION AND RESEARCH DEVELOPMENT**

The use of current Web-based applications to build models in the TLCM-AT environment is critical to the future successful employment of the two tools. The following questions guide this research:

- Can the development of TLCM-AT models be aided using Visual Basic for Applications (VBA) and/or other programming languages?
- What gaps are there between data summarized in SOE DST and data required in TLCM-AT?
- Once a model is built using a VBA interface, how well does the model assess against reality, using failures as the measure of effectiveness (MOE)?
- Given an assessed model and known fluctuations in operational tempo or vehicle population, can the model predict changes in parts failure events?

### **1. Problem Formulation**

The TLCM M&S process involves data gathering, data summary/analysis, and model development and discovery. As a result, many agencies are required to fully

develop a problem statement and subsequent measures of effectiveness. For this research, the talents of many professionals were gathered and melded to produce a universally agreed-upon roadmap.

The International Data Farming Workshop (IDFW) 18 was held in Monterey, California, in March 2009, and presented an opportunity to elicit insight from the attending TLM professionals. A complete report of the conference will be released in the future at <http://harvest.nps.edu/IDFW/18/idfw18.html>. Through IDFW 18, this research drew from the experience and collaborative efforts of many members representing the multiple layers of TLM. MCSC and Headquarters Marine Corps Installation and Logistics (HQMCI&L) are major stakeholders in the Marine Corps' TLM effort. During IDFW 18, MCSC hosted a group focused on exploring the data-to-summary-to-model process.

The IDFW team was made up of a breadth of Marine Corps TLM professionals. As part of the group, Dave Sada from Andromeda Systems represented the Marine Corps' data-gathering element. Alion is the contract holder for SOE DST and was represented in the group by Andy Foote. Clockwork Solutions and Concurrent Technologies Corporation (CTC) are modeling platform developers for TLM; both had modeling professionals attending the workshop. Academic professionals from the Naval Postgraduate School also participated. Finally, the Joint Light Tactical Vehicle (JLTV) modeling and simulation lead from the Program Executive Office for Land Systems attended as an interested customer of TLM. This research was dramatically aided by this gathering of stakeholders in the process. By having all the interested parties participate in a joint effort, a universally accepted process and MOE was determined.

The process for the research was to establish an automated link between the data and the model. Once the link was established, the models were then assessed using root mean squared difference (RMSD) as the MOE based on the opinions of the IDFW workshop and the research sponsor. Once a model was assessed as "good," it was then exercised as a predictive tool. Finally, the model's sensitivity to input factors was tested using Nearly Orthogonal Latin Hypercube (NOLH) Design of Experiments (DOE).

## **2. Link Automation**

This research develops a Bridging Operational Logistics Tool (B-OLT)—an automated link between SOE DST and TLCM-AT. B-OLT is created using VBA in the Excel environment. Housed in Excel, B-OLT is transferable within the Navy Marine Corps Intranet (NMCI) network. B-OLT may be easily expanded to draw input from other databases. Additionally, the concept of a single source document that houses the data necessary to build a predictive model may be expanded to other modeling platforms.

In this research, B-OLT is limited to SOE DST as the single data source and a basic TLCM-AT model. Therefore, the findings are not all inclusive and further research and discovery is required. The opportunities to expand the research are numerous.

## **3. Assess the Goodness of the Automated Model-Build Process**

The models built using the automated process are assessed based on RMSD of modeled and actual parts failures. This goodness of fit is appropriate for a PM and their pursuit of TLCM. Once a model is assessed as reflective of the actual failures that fed the model, it may be exercised to acquire answers to “what if” questions.

For this research, individual models are built and the raw results used to assess the models. These results are presented in a summary of all the models as well as individual TAMCN results. This step may be thought of as a demonstration that a TLCM-AT model can be automatically built and produce reasonable results.

## **4. Initial Examination of Predictive Capacity**

Finally, the automated model-build process is used as a predictive tool. It is known that I Marine Expeditionary Force (I MEF) experienced an increase in vehicle population and operational tempo between 2002 and 2003. The SOE DST data from 2002 was used to build a TLCM-AT model. Once the model was built, the operational tempo and vehicle counts were adjusted to reflect the increase in these two areas that would have been known by I MEF. This model was run for one year (2003) and the results compared to actual 2003 SOE DST data. The initial results are promising. The automated model demonstrates some success using historical data, coupled with expected future changes to make predictions.

## **5. Test Sensitivities by Varying Input Factors**

Once the automated model-build process is assessed, the logical next step is to examine sensitivities of the models to the factors obtained by SMEs. The limitation of data to a single SOE DST source meant that five factors that influence failures were left to other data sources. It is important to determine how much of the model's variation is a result of these factors not resident in SOE DST, in order to determine the possibility of improving the SOE DST platform. Upon completion of an extensive DOE, it was realized that a reasonable portion of the variance for parts failed was captured in the automated model.

In this research, a DOE is conducted and factors of interest are discovered. In reality, models would be assessed, adjusted, and then used to answer "what if" questions. As this was not the purpose of the research, the process is limited to discovery alone in order to demonstrate the concept.

## **F. BENEFITS OF AUTOMATING THE MODEL-BUILD PROCESS**

This research provides a practical interface between two computer-based platforms used by the Marine Corps for TLCM. Once the link between data gathered and models built is established, the models are then verified and the first steps toward validation are taken. In so doing, this research demonstrates the ability to link the two systems in a manner that makes modeling and simulation readily accessible to all PMs in the Marine Corps. Automating the model-build process allows models to be built rapidly, be assessed, and then used for "what if" analysis. Using standardized inputs from SOE DST means the process may be shared across TAMCNs.

## **G. THESIS ROAD MAP**

The following chapters provide the reader with a brief history and possible future of TLCM within the Marine Corps. Chapter II focuses on the SOE DST used by the Marine Corps. Next, Chapter III explains TLCM-AT and its use of stochastic modeling. The TLCM-AT modeling structure demonstrates the complexity of the model and the dynamic answers possible with its effective employment. A bridge between the data the Marine Corps currently collects and the TLCM-AT modeling platform is developed in

this research. Chapter IV describes the methodology for developing the code behind this work and some of the limitations. Once the model is developed using automation, it must be assessed. The assessment and a step toward verification are described in Chapter V. With modeling and simulation comes the natural question of “what data is important?” Chapter VI demonstrates the use of model-building automation in concert with DOE. Finally, in Chapter VII, the insights gained through this research are discussed, along with future research opportunities.



## **II. SOE DST FOR DATA SYNTHESIS AND AWARENESS**

SOE DST is designed to synthesize and present data in an informative manner. The goal is to facilitate trend analysis and assess the current and historical availability posture for Marine Corps systems. The method is data analysis on the maintenance records, with an understanding that the records are often inaccurate or incomplete.

### **A. PURPOSE OF SOE WITHIN LIFE CYCLE MANAGEMENT**

The Department of the Navy's Instruction 5400.15 series defines life cycle management as "management responsibility for a program that encompasses the acquisition program, in-service support, and final disposal" (Winter, 2007). DoD policy is that a system's PM be responsible not only for the acquisition of a system, but also to remain accountable for the sustainment of the system over its lifetime. As directed by MCSC's Strategic Plan 2005-2009, this requires PMs to monitor and improve SOE. Measures of effectiveness include system performance, operational availability, process efficiency, and total ownership costs.

The monitoring of the systems is handled through SOE DST Web-based database, which collects data from a myriad of reporting sources, as illustrated in Figure 3. With this data, PMs can identify areas that require improvement and, through the use of simulation, explore potential courses of action in order to make decisions to improve SOE.

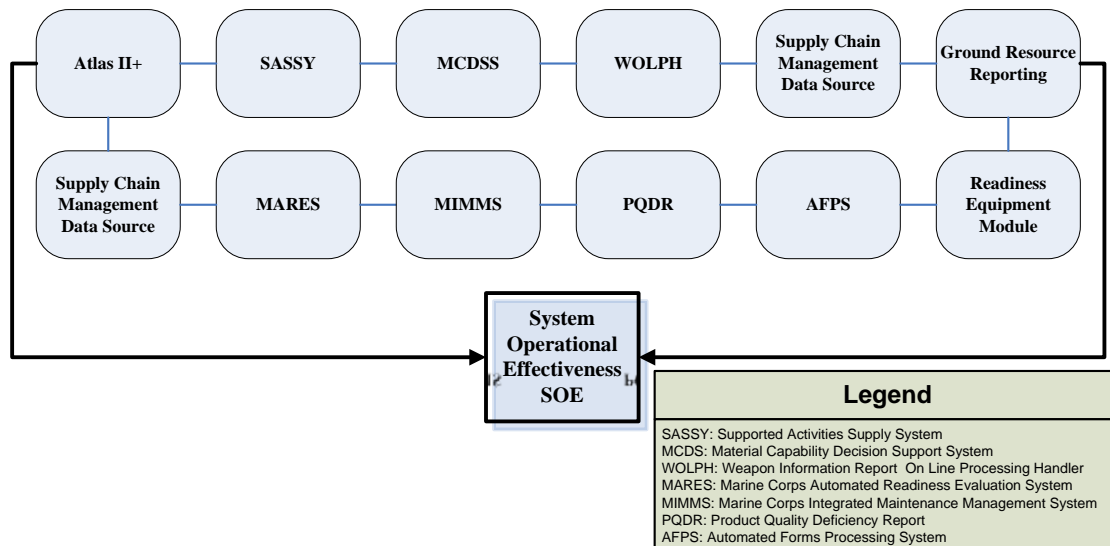


Figure 3. System Operational Effectiveness data-gathering structure.

## B. SOE PROVIDES A PICTURE OF CURRENT POSTURE

Goal three, objective one, of the MCSC 2005-2009 Strategic Plan is to acquire the capability to monitor and improve SOE throughout the life cycle of systems and equipment (Catto, 2005). The mission of the Capabilities Assessment Support Center (CASC) is to serve as the focal point for readiness, reporting, and total life cycle systems management assessments by measuring all performance aspects of fielded Marine Corps ground equipment throughout the life cycle.

To appropriately manage performance, and to answer the first objective of goal three, CASC contracted for the development of the Web-based SOE DST that summarizes and presents data to help PMs evaluate availability and define potential areas of improvement. This Web-based tool captures inputs from 12 data sources (Figure 3) and summarizes that data into trend attributes such as availability, reliability, maintainability, supportability, and total ownership costs. As data is gathered, it may then be used to highlight areas of concern, develop courses of action to address those concerns, and then modeled to help decide which is the most effective.

## C. SOE DST HISTORICAL RECORD OF SYSTEMS MAINTENANCE

SOE DST provides a historical record of a system and all the maintenance and supply-related transactions associated to that piece of equipment. The records are broken down by physical location, part, or single piece of equipment, depending on the user's request. The data is presented in the same repeatable format, no matter the TAMCN or dates requested.

### 1. Display and Synthesis of Raw Data

The "PartsUsage.xls" file from SOE presents a single TAMCN's failed parts for a given time period, in a given location. This Excel file has 13 columns of data for each part that failed in a given time frame, for a given piece of equipment (taken from the SOE DST help file).

- **National Stock Number (NSN):** Unique numerical identifier for each part of the selected equipment.
- **Part Name:** Supported Activities Supply System/Federal Logistics Record (SASSY/FEDLOG) text description of the part.
- **Part Count:** Required number of a given NSN for selected date range. This quantity is bounded by the Stock List (SL)-Quantity of that part.
- **Unit Price:** Current SASSY/FEDLOG part cost for the part.
- **Order Count:** Number of given part ordered during the data range. This quantity is NOT bounded by the SL-Quantity.
- **Extended Price:** Total cost of NSN ordered.
- **Equipment Repair Order (ERO) Count:** Number of EROs that NSN was required during the selected date range.
- **Average Logistics Response Time (LRT):** Mean of the LRT (number of days between date that part is ordered and date it is received) for a given NSN during selected date range.
- **Failure Rate:** Measure of reliability, in failures per million calendar days, for given NSN during selected date range. The failures per million calendar days figure is converted to failures per calendar day when the PartsUsage file is downloaded from the Website.
- **Percentage of Weapons Systems (WS) Replaced:** Measure of percentage of weapon systems (WS) that given NSN was replaced during selected date range.

- **Stock List Quantity:** Identifies total number of given NSN that are required on selected weapon system.
- **Criticality Code:** The criticality code assigned to the NSN.
- **Source, Maintenance, and Recoverability (SMR) Code:** Code associated with the NSN that is used to determine the echelon of maintenance authorized to condemn, repair, or remove and item.

During IDFW 18, it was agreed that the data collected at various points in the maintenance and supply chains can be flawed with user error. Some of the issues include missing/incorrect serial numbers for equipment, incorrect order quantities, missing SMR codes, and a host of others. An important benefit of SOE DST to TLCM is the filtering done behind the scenes to make up for gaps in the data. Once the gaps are filled, averages are presented to the user for various metrics. For the purpose of this research, the most important metric is the failure rate.

## 2. Failure Rates and the Stochastic Modeling Process

Probabilistic and deterministic are two common approaches to modeling and simulation. Deterministic models do not utilize random variables, and are typically more appropriate for use in clearly defined and unchanging cause-and-effect relationships. Scheduling of aircraft may be an example of an appropriate deterministic model approach, in that missions, costs, and benefits are clearly defined and the goal is to decide the optimal combination of scheduling factors. A probabilistic model can capture the random nature inherent in many logistics systems.

In probabilistic models, historical reference may be used to define probabilities after distributions are fitted to the data. Once a model is built in this manner, it allows an analyst to take advantage of historical reference in order to develop an understanding of possible futures to aid in decision-making processes. To ensure that the possible futures are believable, validation of the model is necessary and development of confidence intervals is appropriate. The keystone to a probabilistic model is capturing the right distributions for inputs within the model.

SOE DST provides an average that may be applied to a probabilistic model if the model uses a defined distribution, such as the exponential distribution. Though with

equipment failures it is typical to use a Weibull distribution, to get a less variable picture of potential failures, the exponential is sometimes used (Devore, 2008) as a substitute. The Weibull distribution allows for infant mortality or wear-out mortality depending on a particular part's tendency. Since SOE DST provides an average, the Excel-based file may easily be transferred into inputs into a probabilistic model if an exponential distribution is assumed. Because SOE DST summarizes the data from a larger database, a user of B-OLT cannot derive the shape parameter required to use a Weibull distribution. This may or may not be a factor. For example, when applied to electronic TAMCNs, it may be determined that a Weibull is required. When working with the assembled team at IDFW 18, it was agreed that, given the nature of the legacy JLTV vehicle, using an exponential distribution with analyzed data was more desirable than attempting to reanalyze the same data in order to use a Weibull. Future SOE DST methodologies may aid modeling if shape parameters are computed.

The benefit to using synthesized data from a common repeatable source, such as SOE DST in the modeling process, is that the process of summarizing the data is universal across TAMCNs. This means that a model that effectively uses the SOE DST data for one TAMCN will use the SOE DST data from a different TAMCN in the same manner, with similar results. A model-build process, in turn, that systematically takes the results of SOE DST and translates it into a model may be reused across multiple TAMCNs. Further, if the models are built with the same process, using the same data source, and are repeated over varying conditions and produces statistically similar predictive results, the entire modeling process may be validated over time.

THIS PAGE INTENTIONALLY LEFT BLANK

### **III. TLCM-AT: A STOCHASTIC MODELING PLATFORM DESIGNED TO USE CURRENT DATA FOR QUANTITATIVE PREDICTIONS**

TLCM-AT is a stochastic model platform. The building of models within the TLCM-AT environment relies on data that has been collected, cleaned, and analyzed. One purpose of models built in the TLCM-AT environment is to conduct “what if” analysis designed to gain insight on the impact of potential decisions. This chapter discusses TLCM-AT methodology and processes.

#### **A. TLCM-AT: A MODEL PLATFORM, NOT A MODEL**

The Marine Corps, as part of goal three, objective one of the MCSC 2005-2009 Strategic Plan, requires the capability to use collected historical data to create models useful in “what if” analysis. Clockwork Solutions provided a tool that was originally developed for aircraft maintenance. The sophisticated platform takes user inputs through multiple interfaces and allows the user to determine the effects of policy and management decisions before implementing a change in the real world. This use of simulation reduces the necessity of performing costly trial-and-error testing. TLCM-AT was developed to assist weapon systems fleet managers with evaluating, quantifying, and reducing life cycle costs, without adversely impacting fleet readiness and availability (Clockwork Solutions, 2005). The continuous-loop representation of the life cycle of any weapons system combines operations, maintenance, and logistics, as shown in Figure 4. The blue (inner loop) portions are input variables, while the black (outer loop) portions are outputs from the model. The level of fidelity available with the TLCM-AT model is greater than that of the outputs from SOE DST, which results in some challenges during the model-building that are discussed in Chapter IV.

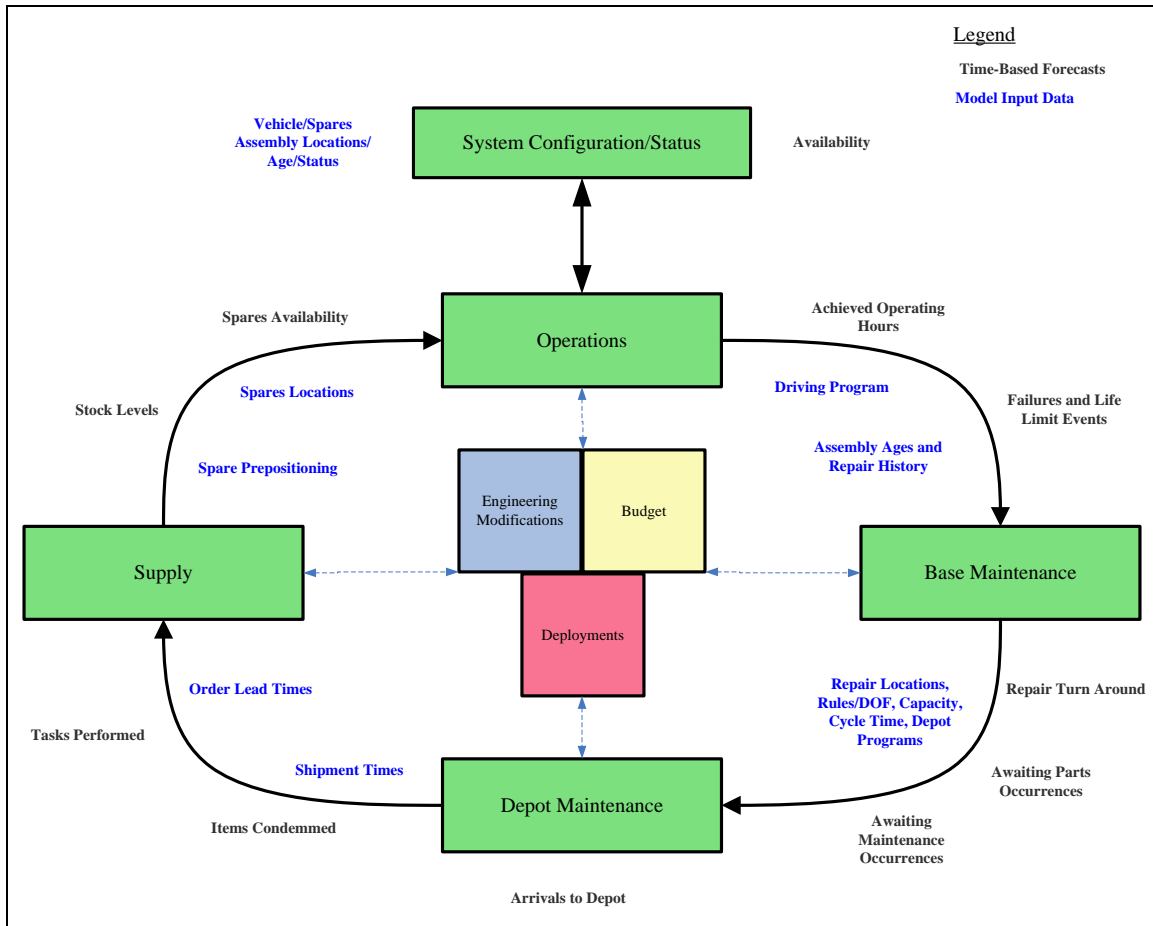


Figure 4. The TLMC-AT continuous-loop model (From: ATLAST Technical Reference Manual, 1992-2005). The outer green boxes represent model modules. Each inner box is an external factor that may effect any of the outer modules. The inner blue terms represent user inputs and the outer black terms are model outputs. This is best viewed in color.

An individual weapons system TLCM-AT model is composed of six interactive components, according to the Clockwork Solutions' technical manual (1992-2005):

- **Initialization:** The initial condition and location of systems and parts in the model; parts or systems in maintenance at the start of the simulation. This is an opportunity to define the age of the fleet, if applicable/possible.
- **System Module:** Work breakdown structure of the system and its variants; the fleet disposition including acquisitions and redeployments; base support structure; three echelon levels, to include ship times.
- **Operations Module:** Current and future operations according to base location, platform type, or serialized system; unscheduled removal rates and life limits.



- **Maintenance Module:** Actions on a component after it has entered maintenance; capacity constraints. Maintenance task times, logistics consequences, and not repairable this station (NRTS) probabilities.
- **Sustainment Module:** Spares, lateral resupply, depot upgrades, and induction programs, reprovisioning.
- **Cost Module:** The cost of purchases and activities, including (but not limited to) maintenance, training, initial and reprovisioning of parts, storage, shipping, and upgrades. There are nine total categories of cost.

## **B. TLCM-AT: INPUT CONSISTENCY CONCERNS**

With the above interactive components come many opportunities to adjust how systems are modeled. As models are not necessarily a reflection of reality, but always a reflection of what is contained in the model, greater accuracy in the model naturally translates into a clearer and more accurate view of eventual reality. The MCSC strategic plan objective calls for a link between the data that is summarized in SOE DST and the model-build process. Removing SME inputs in the foundation of the model, and limiting the inputs to a single data source, allows for repeatability in the process, which is critical to future validation efforts.

### **1. SME Inputs are Often Used, but are not Universally Consistent**

Prior to this research, TLCM-AT models relied on data from a myriad of sources particular to the modeler's span of influence or access. As a result, each model was built, verified, and then used to answer the questions specific to the time the model was contracted. Models could occasionally be reused to answer emerging questions, but not necessarily as a matter of course.

TLCM-AT models are built with available SME inputs and summarized data. Clockwork Solutions has used SOE DST data in the past, with adopted rules for handling gaps and supplementing with SME input. In weapons systems maintenance, SMEs develop a general understanding for the weapons system. As they may be grown in a particular location within a particular operational tempo, they develop expertise in how that weapon system functions in their current environment. Finally, the model-builder may not have access to the best SME. These factors make it essential to

augment the SME in the model-build process wherever possible. This augmentation should come in the form of objective data.

Through B-OLT automation, future efforts may be applied to how the data is gathered and summarized. Additionally, a quantitative analysis may be applied to improving the processes by which the Marine Corps collects, stores, and displays its data.

SMEs are critical when anticipating what may happen in the operational environment. Part of the research was to test the predictive nature of models built. To test this capability, a period of known change was selected and modeled, using only two pieces of information.

- The historical maintenance data taken from SOE DST for the prior year.
- The information that would have been known by an SME in terms of changes in operational tempo and vehicle populations.

To obtain point two, a modeler requires the input that only a SME can provide. The difference in this case is that the SME is providing input particular to the current emerging situation. The historical performance data is still resident in a common picture, single source platform, SOE DST.

## **2. Historical Data Inputs**

TLCM-AT is an Access-based simulation that accepts as much, or as little, detail as required to answer the modeler's question. Prior to the automation of user inputs through B-OLT, developed as part of this research, historical data was left up to the data sources available to the modeler. With SOE DST alone, there are 12 sources for maintenance and supply data. Without continuity of data sources, there is no way to replicate models built between modelers.

The SOE DST Parts Usage file is enough to build a base model. TLCM-AT models have a minimum requirement for the modeler to identify the vehicle platforms, the parts that make the platform (does not have to be complete), the base infrastructure, and failure rates. The models built can also be given shipping times between bases, rules pertaining to lateral support, and a host of other optional factors. The master data

repository (MDR) that houses the maintenance and supply historical data for the Marine Corps contains a majority of the data necessary to at least build a minimal TLCM-AT model.

### **C. TLCM-AT CAN IMPROVE MAINTENANCE PROCESS UNDERSTANDING**

TLCM-AT, or other simulations, may be employed to explore management or policy decisions before committing. This allows decision makers to gain insight to help understand the full consequences of that decision. Once the TLCM-AT model is built and assessed, input factors may be changed to determine potential improvements in measures of effectiveness. Models may also be used to determine what factors may help to improve specified system outputs.

Models that are shown to reflect reality provide insight into possible futures. When decision makers are considering supply positioning options, various courses of action may be modeled to demonstrate the effect on PEI availability, for example. If the possible policy demonstrates a reduction in availability in the model, it is reasonable to assume the same may hold for the real world. This requires that the model demonstrate an appropriate level of similarity to the real world. This confidence comes from repeated use of the model, or the model-build process, and the subsequent accumulated validation.

Similarly, an assessed model may be used to determine where policy may be improved. Through DOE, factors are adjusted in order to demonstrate which are the most influential in explaining the variability of a specified measure of performance. Again, prior to any reliance being placed in the model's insights, there must be some verification of its performance. As stated by the DoD Modeling and Simulation Coordination Office (MSCO), "it is virtually impossible to separately evaluate a model and the data it uses" (Modeling and Simulation Coordination Office, 2006).

TLCM-AT models built using SOE DST data are based in a standardized format. Through the research, it was determined that models built using SOE DST data acted similarly across vehicle variants. This understanding makes it clear that if one can adapt a process of model-building and get expected results, then the process itself can be verified. Further work could, in fact, lead to a validation of the model-build processes, given the standard data source and the model platform.

THIS PAGE INTENTIONALLY LEFT BLANK

## **IV. B-OLT MOVES SOE DATA INTO THE TLCM-AT PLATFORM**

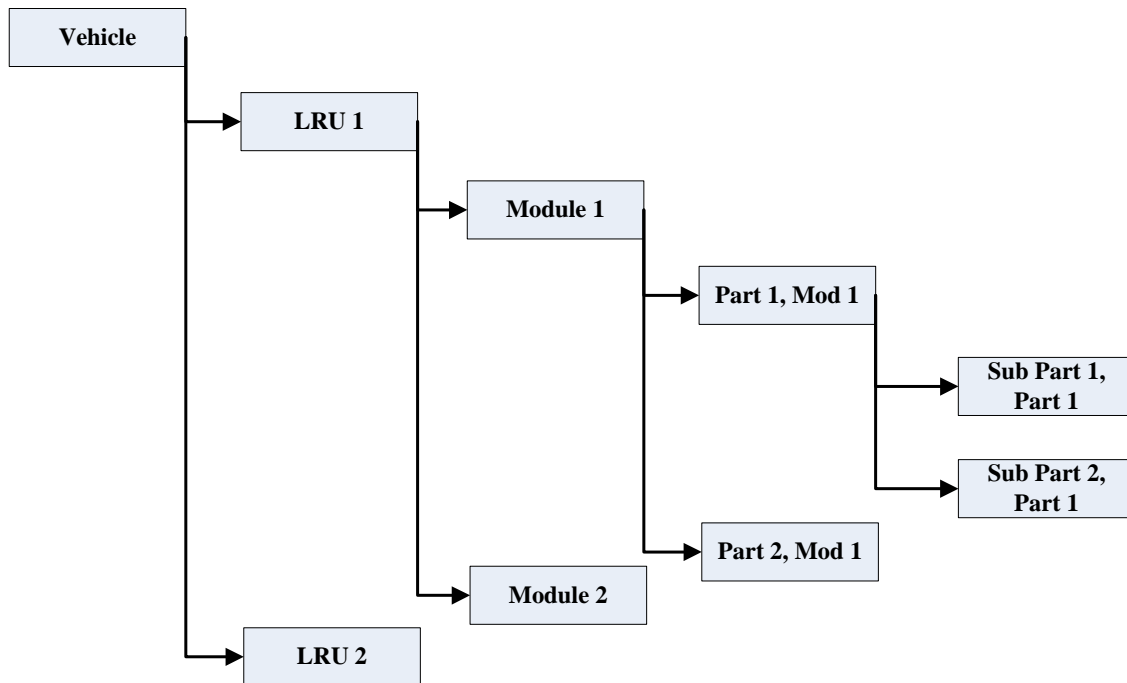
This research initially focused on the model-build process. Old constructs had TLCM-AT models built and “what if” analysis conducted by Clockwork Solutions. While licenses are available to the Marine Corps, the model-build process is currently too complicated to be functionally practical. However, data to feed the model is available to every Marine. SOE DST provides a single document that satisfactorily provides most of the information needed to build a functional TLCM-AT model. The information not resident in SOE DST can be found in Visibility & Management of Operation & Support Cost (VAMOSC) and SME input. This research uses as its research platform the legacy JLTV or High Mobility Multipurpose Wheeled Vehicle (HMMWV).

### **A. SOE DATA CONVERSION TO TLCM-AT**

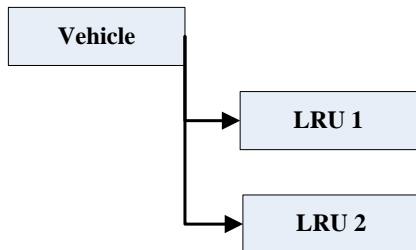
As the lexicon for SOE DST and TLCM-AT are not alike, there are some assumptions that must be made and rules established. TLCM-AT is a series of modules within the overall modeling platform. The system, base, and maintenance modules are the basic modules in the model, and cause some difficulty when converting SOE DST data into a TLCM-AT model.

#### **1. Building the System Module within TLCM-AT**

The system module consists of input data that represents a work breakdown structure of the system and its variants; the disposition of the fleet, including acquisitions and redeployments; and the three echelons of maintenance support structure. Currently, the SOE DST format does not allow for an indenturing of parts within the vehicle, nor does it define parts by part number. As a result, each part that appears on the Parts Usage Report in SOE DST is treated as a line replaceable unit (LRU). For TLCM-AT, all events begin with an LRU event and therefore each part creates tasks on the event list at the start of the simulation. Figure 5 displays the TLCM-AT possible breakdown structure and the limited structure possible using the SOE DST PartsUsage file alone.



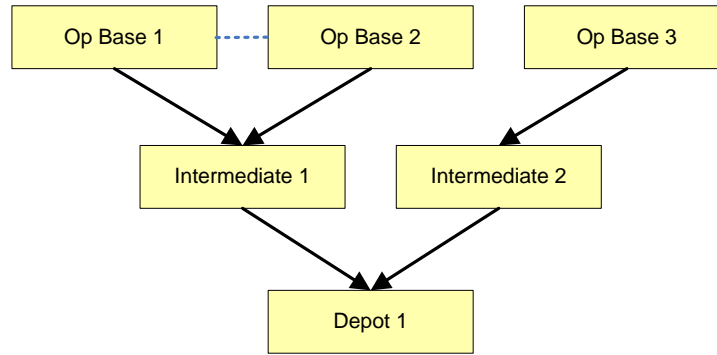
**Work Breakdown Structure Possible**



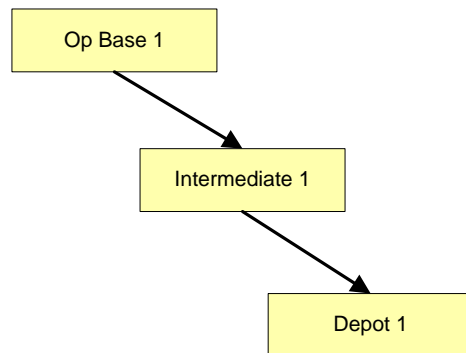
**Work Breakdown Structure using SOE DST**

Figure 5. The work breakdown structure possible in TLCM-AT, as compared to the limited structure in an SOE DST-driven model.

An LRU-only model has the potential to cause large memory storage requirements with the model run. To help offset the storage constraints imposed by an LRU-only model, the model is limited to a single vehicle variant and a single base structure. Figure 6 shows the base structures possible in TLCM-AT and the base structure used to accommodate the LRU-only model using SOE DST data.



**Base Structure Possible**



**Base Structure using SOE DST**

Figure 6. The base structure possible in TLCM-AT, as compared to the limited base structure in an SOE DST-driven model.

The LRU only model limits the scope of future “what if” analysis. Using the single base structure the model cannot exercise lateral resupply or variations in intermediate/depot level supply infrastructure. Having only LRUs identified, the model is limited to the size of the fleet it can model based on memory storage requirements. This unnecessarily limits the dynamics possible within the TLCM-AT environment. As a result, future improvements must include indenturing of parts and the incorporation of a parts number structure within the SOE DST.

## 2. Building the Operations Module within TLCM-AT

The operations module consists of the operational profile, unscheduled removal rates (URR), and life limits. The fidelity is left up to the modeler. In the case of the

operations profile, it is possible to define usage per serialized platform or maybe as general as a defined amount of hours per platform per base. Acceptable units in TLCM-AT are operating hours or miles. There is an option to define two more units, such as number of starts, if necessary. In the SOE DST-based model, there is currently no reliable way to capture average usage rates at any level. This is a function of poor data collection resulting in missing figures when SOE DST conducts its analysis. As a result, this research resorted to VAMOSC figures for average annual miles. In the future, it may be appropriate to include an average annual usage rate within the PartsUsage file of SOE DST.

The SOE DST equivalent for the URR is the failure rate. When a user downloads the PartsUsage file from SOE DST, they are provided a failure per day rate for each part. For TLCM-AT, failures are treated as a Weibull distribution. SOE provides an average failure rate across the fleet. Without the raw data, a B-OLT user cannot compute the shape parameter. Without knowing a shape parameter, SOE DST-driven TLCM-AT models use the exponential distribution (i.e., we assume a shape parameter value of 1). Additionally, TLCM-AT works with failures per kilo-miles and the SOE DST failures per day must be converted using the following formula:

$$\frac{1 \text{ Failures}}{\text{Day}} * \frac{91.25 \text{ days}}{\text{Qtr}} * \frac{1 \text{ Qtr}}{X \text{ kilo-miles}} = \frac{\text{Failures}}{\text{kilo-miles}}$$

Once the failures per kilo-mile are determined, the miles per hour (mph) must be determined to get an estimated depiction of system-level operational usage. An SME opinion of the average speed the vehicles travel is required, as SOE DST does not currently provide this information. In garrison (noncombat) operations it is presumed that vehicles drive at an average 20 mph rate. In combat, this figure is boosted to 35 mph. With the VAMOSC-provided average miles driven and the SME-provided mph estimates, the operations module may be created.

### **3. Building the Maintenance Module within TLCM-AT**

The maintenance module accepts inputs pertaining to logistics consequences, maintenance task times, and NRTS events. NRTS is a TLCM-AT-specific acronym that allows the model to address cases when a component must be evacuated to the next



higher echelon of maintenance. Typically, with Marine Corps maintenance, this is tied directly to the specific part requiring maintenance.

The maintenance cycle begins with an LRU event that is caused by the unexpected removal rates and life limits definitions provided in the operations module. The end of the maintenance cycle depends on the object of interest. A platform is out of the maintenance cycle when all of its slots (defined in the system module) are filled with operable parts.

When there is an LRU event, the first step is an inspection of the vehicle, which always occurs in the operational level. The inspection results in four possible object statuses: operational, no-fault-found, repairable failure, or nonrepairable failure. Since the maintenance cycle begins with an LRU event, the LRU is removed from the platform and inspected first. Based on the possible status, the following will result:

- **Operational:** LRU is never removed and the platform immediately goes back in the operation cycle.
- **No-Fault-Found:** LRU removed, inspected, and replaced in the platform, as if it were determined to be operational.
- **Repairable Failure:** LRU is removed and replaced in the platform if there is a spare LRU available. The LRU enters the maintenance cycle. A module, part, or subpart is determined to be damaged and that module, part, or subpart is removed from the LRU. The module, part, or subpart is entered into the maintenance cycle. If a replacement is available, the LRU's defective part is replaced and LRU is put back into the platform (if no spare LRU was previously available) or into shelf stock.
- **Nonrepairable Failure:** Same as repairable failure, but the LRU is discarded and new part installed.

The maintenance cycle from LRU event to repair may be seen in Figure 7.

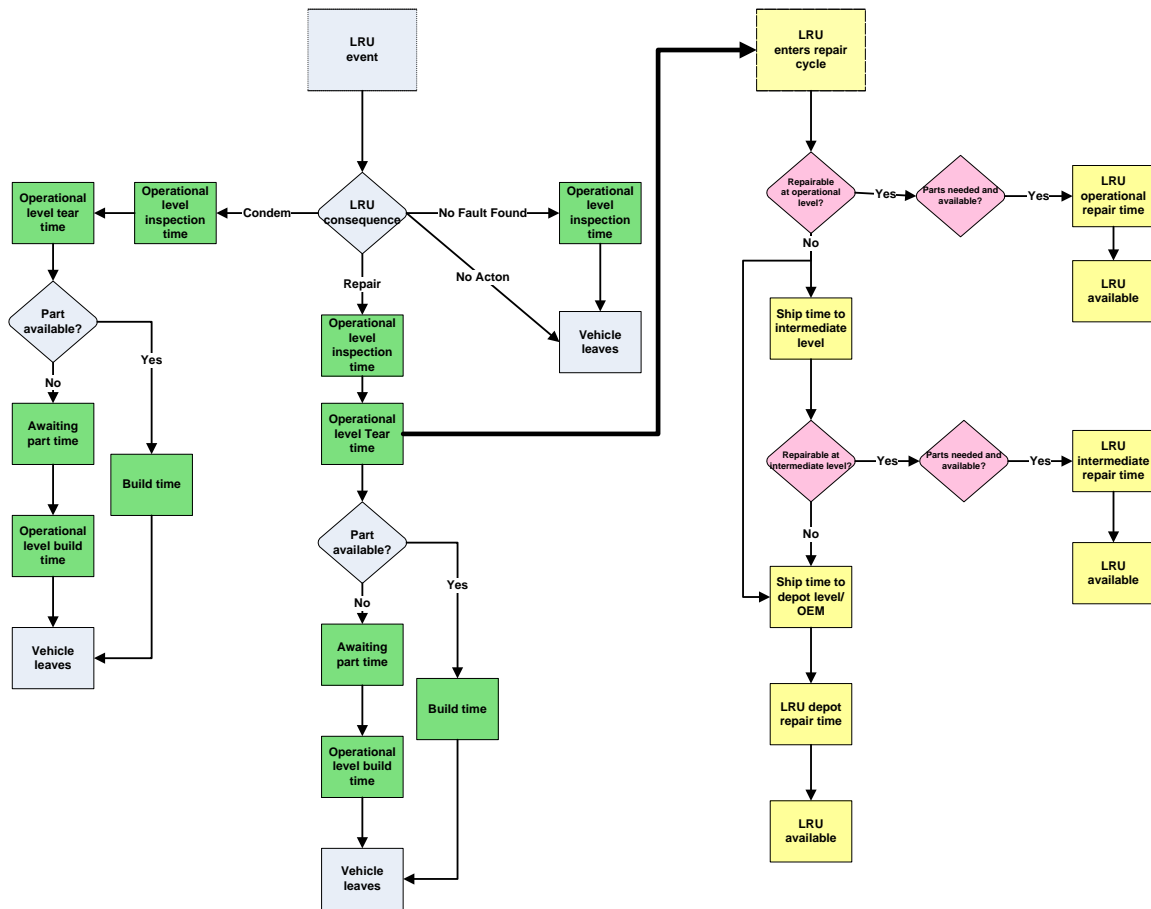


Figure 7. The maintenance flow module in TLCM-AT. This is best viewed in color.

For the SOE DST-based model, the SMR codes are used to define logistics consequences. Inspection times are based on the third digit of the SMR code, which, according to NAVSUP 7-19, is the lowest maintenance level authorized to remove, replace, and repair the part. The model logic allows times to be allocated for inspection, repair, and shipment. The Maintenance Allocation Chart (MAC) associated with every TAMCN provides expected times to perform maintenance tasks. For the legacy JLTV, the MAC is found in TM 9-2320-280-20-3. Table 1 defines the high and low times associated to inspections, repairs, and tear times, based on which level of maintenance is allowed to repair or replace the item. Currently, there is no distribution associated with these times.

Table 1. Inspection time, in hours, assumptions applied to an SOE DST-driven model.

Action	MAC Nomenclature	Range	1 <sup>st</sup> Echelon	2 <sup>nd</sup> Echelon	3 <sup>rd</sup> Echelon
Inspection	Inspection and Test	Low	0.0	0.2	0
		Avg	0.18	2.0	0
		High	0.7	2.0	0
Repair	Overhaul, Repair and Service	Low	0.0	0.0	0
		Avg	0.63	3.8	0
		High	3.5	16.0	0
Tear	Install and Replace	Low	0.0	0.0	0
		Avg	1.1	3.2	0
		High	10.0	32.7	0

The tear times are used to define how long it takes an object to be removed from the platform. Since B-OLT creates an LRU-only model, and there is no flexibility in defining separate removal rates based on indenture, additional time had to be added to parts that are typically evacuated to a higher echelon of maintenance. An LRU in the TLCM-AT logic is removed at the operational level. If it is NRTS, then it is evacuated to the next higher echelon of maintenance and the modules that are defective within the LRU have their own associated intermediate- or depot-level tear times. However, given the limits of an SOE DST-based model, the shipping times had to be added to the operational tear times. It is important to remember that each LRU is removed at the operational level. Table 2 demonstrates the time added to tear time in TLCM-AT to account for shipping the part or PEI to the appropriate echelon of maintenance.

Table 2. Tear time assumptions applied to an SOE DST-driven model.

Lowest Remove/Replace	Ship Time to Repair Level	
	Single	DOE range
Operational	0	0
Intermediate	5 days	1-20 days
Depot	30 days	20-60 days

It is possible for each part to define maintenance allocation times based on the maintenance allocation charts. However, the legacy JLTV MAC does not define parts by NSN and therefore there is no practical way to merge SOE DST data with MAC. The MAC nomenclature does not match the nomenclature used in SOE DST and there are

multiple NSNs that may or may not be the same part. Without a clear understanding of the indenture structure and which parts require how much time, based on MACs, the SOE DST-based model is limited to approximations of times, based on echelon of maintenance categories.

#### **4. Building the Sustainment Module within TLCM-AT**

The sustainment module allows for shipment times, spares allocation, lateral resupply, preferred buys, and a depot upgrades program. The SOE logistics response time is the average ship time for that repair part and can be used as shipping times. This is only true if, in reality, there are never spares on hand. For the model, it would be best to fit a distribution to all LRUs (perhaps separated by criticality code) and use this as the shipping time. Given the limitations of SOE DST and an interest in capturing all possible failures, the models associated with this research flooded the supply system with 100 parts at each level of maintenance. By always having a spare part in the system, there was no doubt that the modeled vehicles would achieve their defined operational tempo and would, therefore, break as often as possible.

#### **B. B-OLT CODING IN VISUAL BASIC FOR APPLICATIONS (VBA)**

B-OLT is established in an Excel environment and executes using VBA code. The driving factor behind Excel implementation is the universal acceptance of Excel by potential users. B-OLT can be placed on any machine in the NMCI network that has the TLCM-AT platform installed and run without requiring the user to learn the TLCM-AT application. However, assessment of the model built must be done prior to conducting any “what if” analysis. For this reason, PMs must work in concert with modeling professionals employing any simulation. The overall place for B-OLT is between SOE DST and TLCM-AT to bridge the gap between data collected/summarized and simulation as demonstrated in Figure 8.

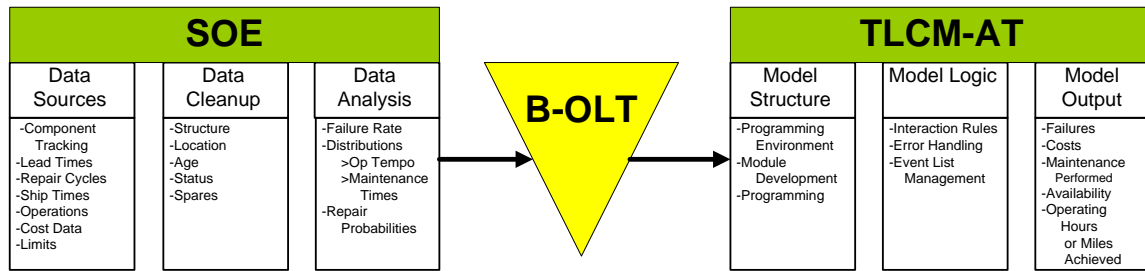


Figure 8. The link developed with B-OLT between data and simulation.

B-OLT links the SOE DST Excel document with limited user inputs to the Access-based TLCM-AT platform. The user interface fills gaps in the SOE DST PartsUsage file data. Specifically, the user must provide maintenance times (from MAC), shipping times (from SME), annual miles (from VAMOSOC), average mph (from SME), and minimum dollar value of interest (from SMEs). The minimum dollar value of interest is aimed at helping computational time. In this research, the parts that are reported on the PartsUsage file with a value less than the minimum are consolidated prior to model-build. It is recommended that future SOE DST PartsUsage files contain this data in order to create a more standardize model-build process.

THIS PAGE INTENTIONALLY LEFT BLANK

## V. B-OLT-DRIVEN MODELS ASSESSMENT

We need to assess the quality of the models built using B-OLT. This assessment involves checking the model's ability to produce reasonable results based on consistent inputs. Once assessed, a validation of the model may begin. The following describes the assessment and validation of the B-OLT-built models.

### A. VERIFICATION/ASSESSMENT: MODELED FAILURES COMPARED TO DATA HISTORY

The automated-build process is assessed using five separate HMMWV variants: D1001, D1002, D0187, D1125, and D1159. The populations used are those of the entire Marine Corps. By using the entire Marine Corps, the computed failure rates can be consolidated and are not directly influenced by specific environment factors that may or may not be present in one location or another. A total of five models are built and run. The MOE is each model's ability to replicate the modeled year's failures.

The proportion of difference was computed with  $\frac{ModelUER - SOEPartCount}{SOEPartCount}$

where Model UER is the modeled failures and SOEPartCount are the actual failures. The results are presented in Figure 9. The chart displays the distribution of the difference between modeling and actual failures. The larger bars demonstrate more occasions when that particular value was reported. The percent difference distribution figure shows that the average percent difference is around 30%. With an average of 30% difference between real and actual failures, the results seemed disappointing. There was reason for concern with vehicle populations, and adjustments were made.

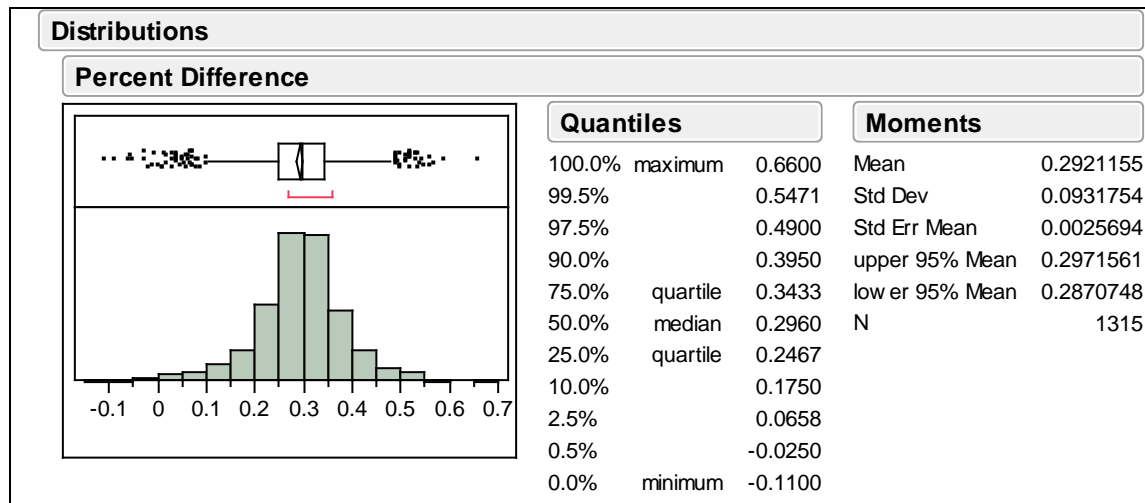


Figure 9. The distribution of proportion difference between the actual failures and modeled failures.

The outliers tend to be those parts with a high number of failures and, because the part counts directly impact the failure rate in SOE DST, these are also the parts with a higher failure rate. The D1125 and D1159 have the largest populations' numbers and the largest standard deviations. Given that the vehicle populations come from the serialized count document from SOE DST, but the URR computation comes from an adjusted vehicle population based on rules within SOE DST, it is reasonable to assume the vehicle populations are misrepresented in the first draft of the model.

The average percentage difference for D1125 and D1159 was 32% and 30%, respectively, while the percent difference for D0187 was 11%. Because SOE DST does not contain the number of vehicles used to calculate failure rate, it is possible the original model contained an inappropriate number of vehicles. The D1125 and D1159 models were re-created. The vehicle populations for D1125 and D1159 were reduced by 20% of their original count and a better-assessed model resulted. Figure 10 shows the new distribution of proportion differences that result from the adjusted populations. Once a reasonable percent difference was achieved, actual difference numbers were examined.



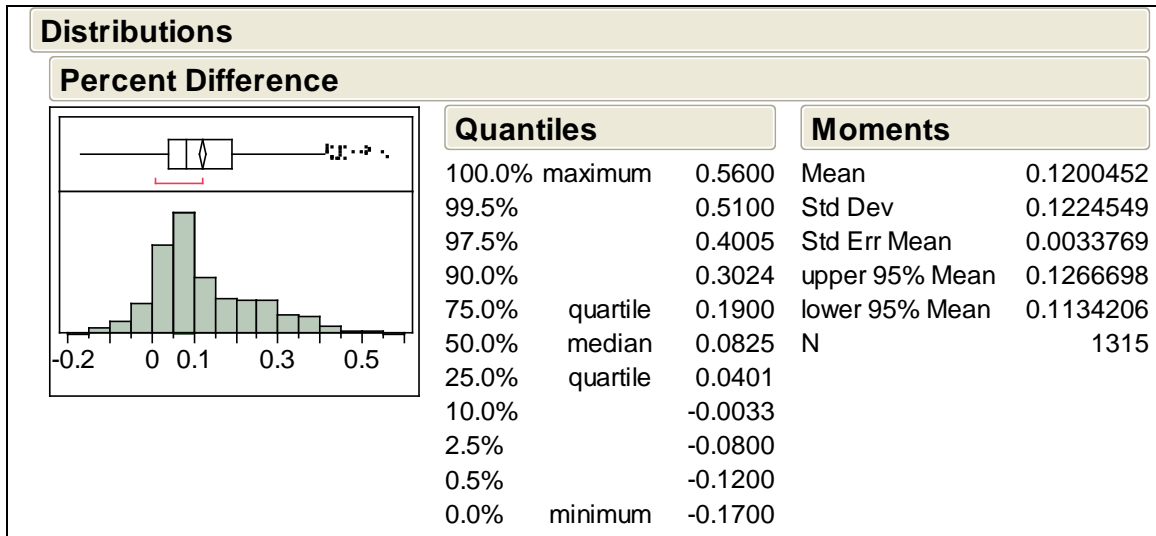


Figure 10. Proportion difference on adjusted vehicle population actual failures v. modeled failures.

For each variant, the actual difference between real and model parts failures was computed. The computation for literal difference ( $ModelUER - SOEPartCount$ ) results in a better picture of what the real difference is between the models' failures and real failures. Figure 11 shows the results taken from all TAMCNs at the Marine Corps inventory levels after D1125 and D1159 vehicle counts are adjusted. For a total of 1,315 parts, the models had a mean actual difference of 0.53. This mean difference is the average difference of modeled failures from real failures. Given that the tool will be used to project maintenance parts requirements, the overestimation is desirable. Smart over-provisioning will ensure parts are available for repairs, while not stressing embarkation or budget restraints.

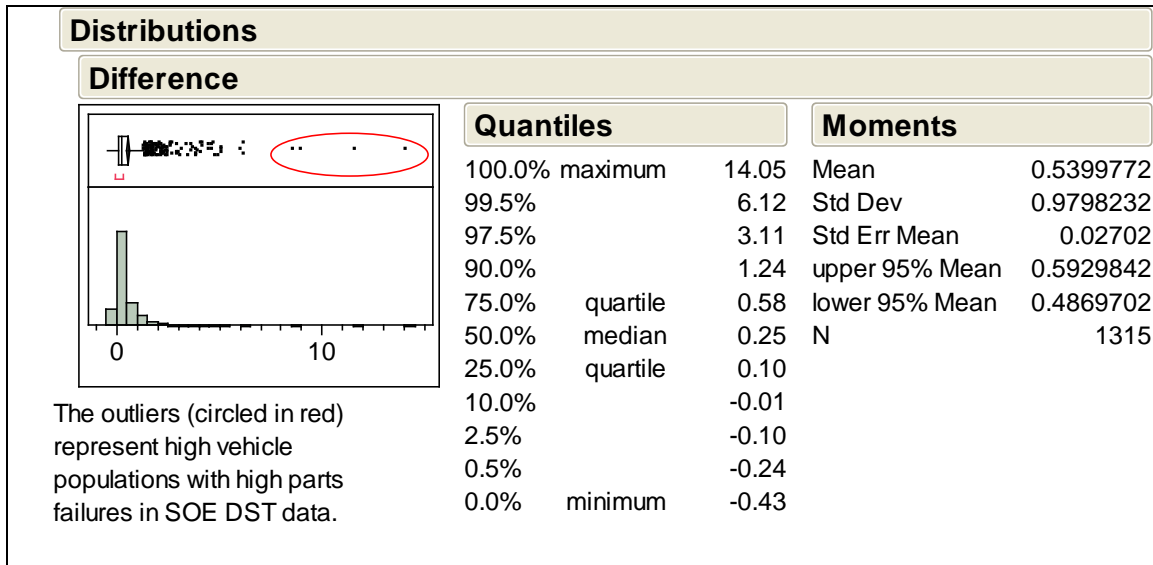


Figure 11. Distribution of Model Failures–SOE DST failures across TAMCNs in the Marine Corps total population. The model is overestimating failure events in general.

While the outliers are of concern, the overall results are promising. The outliers are all parts with high part counts and high vehicle population counts. However, having a model that assesses this well would provide a practical tool to answer “what if” questions. For example, if the Marine Corps had a chance to switch vendors for a particular part that promised a better failure rate, the effects of that adjustment could be, at least, roughly quantified.

Figure 12 shows the correlation between the URR, part count, and difference in the models. Correlation is the degree of linear association between factors (Devore, 2008). Here, a correlation of 0.71 suggests that high URRs are associated with high differences between modeled and real parts failures. As more failures accrue, the distance between reality and model increases.

Correlations			
	URR	Part Count	Difference
URR	1.0000	0.7092	0.7040
Part Count	0.7092	1.0000	0.9958
Difference	0.7040	0.9958	1.0000

Figure 12. The correlations between URR, Part Count, and Difference across all TAMCNs.

## B. FURTHER EXPLORATION OF ALL REGIONAL ACTIVITIES CODES MODEL

Once reasonable models were developed, regression analysis was conducted. For the analysis, the removal rate, vehicle count, annual miles, and average miles per hour were considered. The output analyzed is the difference between actual and modeled failures. The analysis is done in JMP® using a step-wise regression.

Sorted parameter estimates, like the ones in Figure 13, present the factors in descending order, from most to least significant. The significance is measured with the t-ratio. An absolute value t-ratio of greater than two rejects the hypothesis that the factor is zero (Devore, 2008). If the factor is zero, it is meaningless in the computation of the, in this case, failures recorded and subsequent difference from reality.

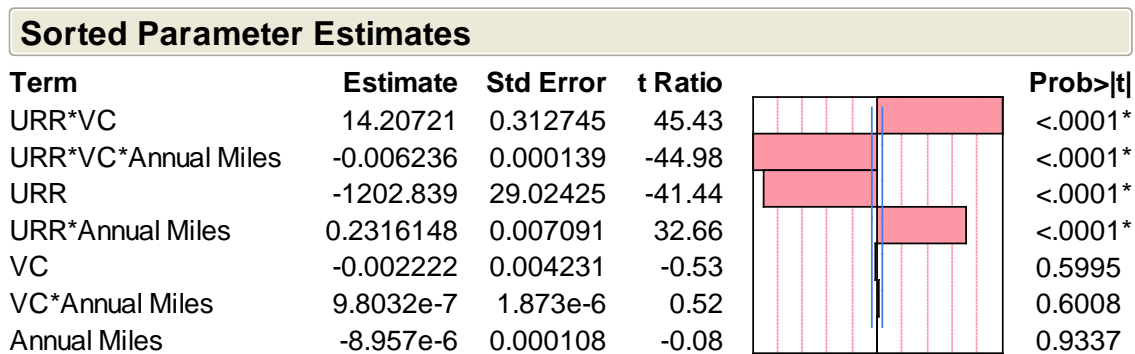


Figure 13. Parameter estimates for all RACs data for all TAMCNs.

When the SOE DST-driven model is verified, there are interaction factors relevant to the outcome. Correct URR figures allow the model to be properly affected by other factors, such as the number of vehicles with those parts and the miles driven by those vehicles. Two points may be made:

- The wrong URR will cause the model to drift away from reality.
- If the correct URR is captured, the number of vehicles and miles driven impact the assessment strength of the model.

As the number of parts that failed during the period increases, so does the difference between what failed in the model, as compared to reality. There are pairwise correlations that explain why URR is the most significant factor. When SOE DST

computes failure rates, it is a function of uptime and the number of parts that have failed during the given period. Uptime is determined by vehicle and is the number of days a serial number is available for operation. Correlations between VC and annual miles driven are reasonable. The correlations show that there is interaction between these factors and the model makes sense. The positive correlation indicates that as the URR, miles driven, and vehicle counts increase in reality, the deviation from reality is expected to increase. Since URR is a function of the number of parts that have failed during the given period, increased numbers of failures means an increase in deviation from reality within the model as well. Finally, these all demonstrate the importance of the URR (e.g., failure rate) within SOE DST being as accurate as possible.

### **C. STEPS TOWARD VALIDATION: PREDICTIONS MADE BY VERIFIED MODELS**

In 2003, I MEF deployed to Iraq with a portion of their legacy JLTV assets. The MEF's overall vehicle population increase was known. VAMOSOC provides a deployed and garrison annual-miles driven rate. SME input suggests the speed of deployed vehicles increased to an average of 30 mph. SOE DST-driven TLCM-AT models were built using B-OLT and 2002 data. These models were then run by increasing the vehicle counts and the operational tempo within TLCM-AT—with surprising results.

#### **1. Known Changes Key in Testing Prediction Capability**

For meaningful validation, the results that the model is to be compared with must be known, but not used to build the model. Data for 2003 were not used in the creation of the 2003 models; however, to test the model's predictive capacity, it must be presumed that some elements would be known. For this research, the following was assumed to be known in 2002:

- 2002 SOE DST data.
- Vehicle numbers for the deployment.
- An estimate for miles to be driven in 2003.
- An estimated average speed.

In 2002, I MEF was given the mission to deploy to Iraq. Prior to leaving, they received an increase in equipment allocations and could estimate that their operational tempo would increase. For this research, VAMOSC was used to get average annual miles for deployed legacy JLTV assets. The MDR was used to get reporting quantities of legacy JLTVs for the MEF during 2003. Both data elements would have been known, or could have been estimated, in 2002.

The 2002 model was built and assessed. The known changes (count, miles, mph) were then changed in the assessed model. In so doing, the SOE DST-driven TLM-AT model, built using B-OLT, was able to “predict” 2003.

## **2. The Model Demonstrated an Increase in Failures Based on Known Expected Operational Tempo Changes**

The B-OLT model was subject to some limitations. As discussed earlier, SOE DST only reports on failures that occurred during the time frame requested. Therefore, in the 2002 to 2003 prediction, there were parts that failed in 2002 that did not fail in 2003. Additionally, there are multiple NSNs that represent the same part. These two facts combined made it impossible to thoroughly investigate the model’s predictive capacity. Prior to models being built, 2002 and 2003 PartsUsage files were compared and only those NSNs in common between the two years were modeled.

Given the limitations, there were still insights to be gained by comparing the predicted failures with the failures experienced during 2003. The NSNs that failed in 2002 were modeled in the 2003 model. All modeled failures’ NSNs were compared to 2003 SOE DST PartsUsage file Parts Count. There were 297 total parts that were modeled across the TAMCNs. From these 297 parts, the mean absolute difference was 2.52. Again, this difference was a conservative estimate, and would ensure that more parts are available for repairs. The correlations, in Figure 14, demonstrate again the reliance on the URR and total failures.

Correlations			
	UER Total	URR	Difference
UER Total	1.0000	0.7949	0.7329
URR	0.7949	1.0000	0.7994
Difference	0.7329	0.7994	1.0000

Figure 14. The correlation coefficients of the number of part failures, URR, and the difference between model and reality. The prediction exercise shows promise and the correlations suggest where improvement can be made.

Given the current predictions from the model, as built from existing SOE DST data, a provisioning package could be made. Specifically, the UER (modeled failures) quantities could be used to draw a Class IX block. If the UER quantities were taken plus one, two, or three standard deviations, the results would be as pictured in Figure 15. Along the x axis are the results of UER-Parts Count computation. The results show that going just one standard deviation more than the model's prediction would have resulted in being short on only 17 of 297 parts during the provisioning period.

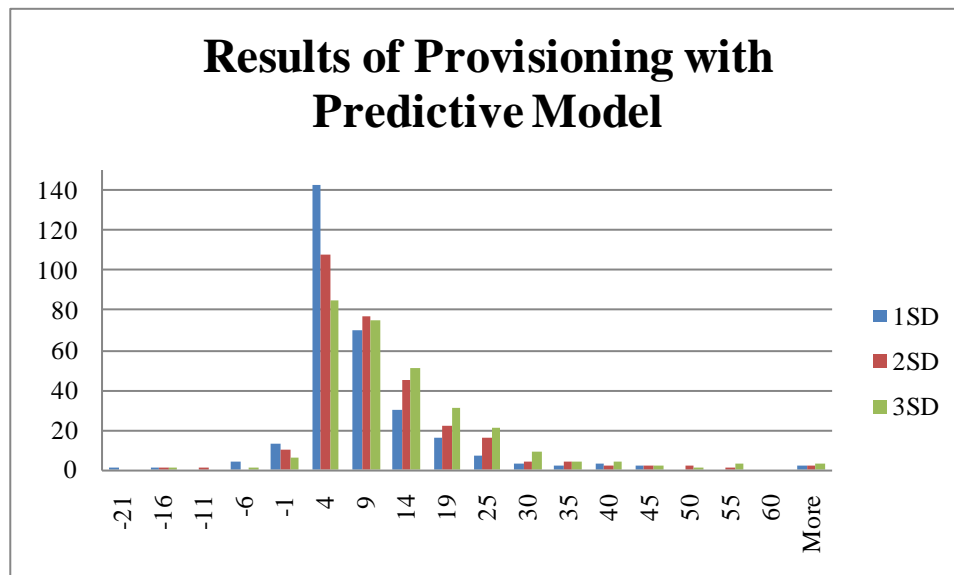


Figure 15. The results of provisioning with predictive model. The columns represent one, two, or three standard deviations above the modeled requirement minus the actual requirements in 2003.

Until SOE DST reports failure rates for all components of the PEI, and multiple NSNs can be linked to a common part number, true measures of predictability will be

impossible. The limited tests, while promising, are just a first step toward validating and using the B-OLT models as a predictive tool. To prepare for the eventuality of employing these tools in a predictive capacity, it was reasonable to test the sensitivity of the B-OLT models to the factors that were not directly obtained from SOE DST.

With assurance that the model was acting as expected, a logical next step is to explore sensitivities to those factors that are being estimated in the model. For the SOE DST-driven TLCM-AT model, those factors are:

- Annual miles driven.
- Vehicle count for each population.
- Average MPH.
- Probability that a part will not be repairable.
- Unexpected remove rate.

The next step is to develop a DOE to saturate the design space in a most efficient manner to test sensitivities to the factors of interest listed above.

THIS PAGE INTENTIONALLY LEFT BLANK



## VI. MODELS' SENSITIVITY TO INITIAL FACTORS

During the assessment of the models, factors were identified that might influence the MOE. These factors are explored using DOE. The DOE methodology is explained and results presented.

### A. NEARLY ORTHOGONAL LATIN HYPERCUBE (NOLH) DESIGN EXPLANATION

The NOLH DOE is capable of saturating a design space to discover factors of importance. To test a response variable's sensitivity to specific factors, a design should be made to ensure little or no correlation between factors. In making the design points nearly orthogonal through an NOLH DOE, the estimates of the coefficients in the associated regression models are uncorrelated (Cioppa & Lucas, 2007). The model sets described in this chapter were all created using a NOLH design.

### B. GENERAL DOE FOR SENSITIVITY ANALYSIS FOR FACTORS USED IN THE MODEL-BUILD

An efficient DOE was developed using NOLH designs. These DOEs were run using the SOE DST PartsUsage file pulled for TAMCNs D0187, D1001, and D1002. Records for all Regional Activity Codes (RACs) in the Marine Corps were used. Accordingly, there were three model sets developed in the research associated with this portion of the thesis.

There were some common design factor ranges for all legacy JLTV variants and they are displayed in Table 3 as they were used in the NOLH design.

Table 3. NOLH DOE factors that are common between all TAMCNs.

	<b>ProbCon</b>	<b>MPH</b>	<b>RateChange</b>
<b>Low</b>	0.1	20.0	0.5
<b>High</b>	0.99	50.0	2.0

Probability of condemnation (ProbCon) is the probability that a repairable part will not be repairable and will need to be replaced. As discussed earlier, the URR is derived from the SOE DST's failure rate and is equivalent to the inverse of Mean Time

Between Failure (MTBF). In order to vary this within the DOE, each URR was multiplied by a uniform rate change between 0.5 and 2.0. Finally, mph was varied from 20 to 50, based on SME input.

The annual miles driven and the vehicle population factors were also adjusted in the DOE. The high and low values for these ranges were dependent on the original value. For annual miles, VAMOSC provided the average miles driven in garrison environments. This figure, by TAMCN, was adjusted to plus or minus 1,000 and is used as the high and low of the range, respectively. Vehicle populations were taken from the SOE DST's serialized location report. The figures provided by SOE DST were then adjusted plus or minus 30% for the high and low of the range, respectively.

TLCM-AT, when defining the URR, allows the user to incorporate two parameters for the Weibull distribution. If a shape other than one is used and the MTBF is also adjusted, the result is an unclear representation of the effects of the shape on the MOE. In general, if an exponential distribution is used instead (Weibull with shape = 1), the result will be a distribution with wider variation. Since the worst-case scenario is acceptable, the shape parameter was not used as a factor of possible interest.

## **C. SENSITIVITY RESULTS**

For D0187, 17 design points were run with vehicle counts that represented the population for all RACs. Each design was run for a total of 100 histories. A 5-factor design can be executed with just 17 design points. The NOLH was set up, and the model was run, using the initial 17 design points. An example of the design can be seen in Figure 16. The data in green are the user's inputs. Each row below corresponds to a given design point. The columns contain the factor settings across the design points.

<b>low level</b>	<b>794</b>	<b>187</b>	<b>0.1</b>	<b>20</b>	<b>0.5</b>
<b>high level</b>	<b>2794</b>	<b>347</b>	<b>0.5</b>	<b>50</b>	<b>2</b>
<b>decimals</b>	<b>0</b>	<b>0</b>	<b>2</b>	<b>0</b>	<b>1</b>
<b>factor name</b>	<b>AM</b>	<b>VC</b>	<b>ProbCon</b>	<b>MPH</b>	<b>RC</b>
1	1419	347	0.43	31	0.9
2	919	227	0.45	37	0.5
3	1044	257	0.13	28	1.4
4	1169	287	0.23	50	1.3
5	2294	337	0.28	24	1
6	2794	237	0.25	44	0.6
7	2044	217	0.5	29	1.8
8	1919	327	0.4	48	1.7
9	1794	267	0.3	35	1.3
10	2169	187	0.18	39	1.6
11	2669	307	0.15	33	2
12	2544	277	0.48	43	1.1
13	2419	247	0.38	20	1.2
14	1294	197	0.33	46	1.5
15	794	297	0.35	26	1.9
16	1544	317	0.1	41	0.7
17	1669	207	0.2	22	0.8

Figure 16. The NOLH DOE produced for the D0187.

The IDFW 18 group decided that the best MOE when assessing the model-build process was the model's deviance from reality in terms of parts failures. This translated into a RMSD computation.

For each design point, there is a root mean square error computed for the difference between how many parts actually failed and how many parts failed in the

model. Root mean squared difference (RMSD) = 
$$\sqrt{\frac{\sum_{Parts} (ModelUER - SOEPartCount)^2}{n_{parts}}}$$
,

where Model UER are the modeled failures, and SOE DST PartCount are actual failures for the given time period, model, and population. This difference is squared and normalized, and the sum taken from across all parts associated to that TAMCN. This figure allows an overall MOE of that design point to return an expected result according to how it compares to the actual failures experienced in reality.

Initial results were not promising. The model-build process rolls up all parts that cost less than \$10 into a single part line number. This is done to ensure that computation limits are not exceeded. Remember that TLCM-AT populates an event list based on the failure rates of each LRU. With no indenture structure provided in SOE DST, the models built for this thesis are LRU-only models. During the post analysis, it was discovered that the line item for the consolidated parts contributed a lot of variability into the model. This is a result of the wide range of failure rates associated to the individual parts that make up this consolidated parts line. Once this line was deleted from the analysis, the RMSD analysis made more sense.

Correlations again were examined first to determine which factors were correlated with the RMSD. In Figure 17, the following abbreviations apply:

- **AM:** Annual miles, the miles driven during the simulation.
- **VC:** Vehicle Count, the number of vehicles in the simulation.
- **ProbCon:** The probability of a repairable part being condemned.
- **MPH:** Miles per hour.
- **RC:** Ratio Change. The computed URR is multiplied by this factor to represent an incorrect URR.
- **RMSD:** Root mean squared difference.

Correlations						
	AM	VC	ProbCon	MPH	RC	RMSD
AM	1.0000	0.0000	-0.0000	-0.0079	0.0268	-0.0120
VC	0.0000	1.0000	0.0000	0.0039	0.0161	0.3401
ProbCon	-0.0000	0.0000	1.0000	-0.0091	0.0160	0.0266
MPH	-0.0079	0.0039	-0.0091	1.0000	-0.0296	-0.0016
RC	0.0268	0.0161	0.0160	-0.0296	1.0000	0.6487
RMSD	-0.0120	0.3401	0.0266	-0.0016	0.6487	1.0000

Figure 17. The correlations in the NOLH DOE performed on the D0187 variant. The positive correlation between RMSD and RC indicate that an increase in RC will result in a larger overall change in the model's ability to back validate well.

The correlations are displayed to demonstrate the orthogonal nature of all the input factors. This is a result of the careful DOEs using an NOLH. It can be seen that the individual

factors do not share correlation. Correlation between a factor and RMSD demonstrates that factor's linear effect on the eventual outcome.

D1001 and D1002 were run through the same fundamental DOE. The only change was that a stacked design was used, so there were 34 total design points for the D1001 and D1002 models. The correlation matrices are in Figure 18. The URR remains a factor in all models; however, the degree of influence varies considerably between the models.

Correlations							Correlations						
	AM	VC	ProbCon	MPH	RC	RMSD		AM	VC	ProbCon	MPH	RC	RMSD
AM	1.0000	0.0000	0.0000	0.0033	0.0268	-0.0128	AM	1.0000	0.0000	0.0000	0.0033	0.0268	-0.0088
VC	0.0000	1.0000	0.0014	0.0119	0.0048	-0.4432	VC	0.0000	1.0000	0.0007	0.0078	0.0065	0.2778
ProbCon	0.0000	0.0014	1.0000	-0.0085	0.0187	-0.0272	ProbCon	0.0000	0.0007	1.0000	-0.0085	0.0187	-0.0398
MPH	0.0033	0.0119	-0.0085	1.0000	-0.0195	-0.0237	MPH	0.0033	0.0078	-0.0085	1.0000	-0.0195	0.0211
RC	0.0268	0.0048	0.0187	-0.0195	1.0000	-0.7332	RC	0.0268	0.0065	0.0187	-0.0195	1.0000	0.3848
RMSD	-0.0128	-0.4432	-0.0272	-0.0237	-0.7332	1.0000	RMSD	-0.0088	0.2778	-0.0398	0.0211	0.3848	1.0000

Figure 18. The correlation coefficients for the D1001 (left) and D1002 (right) variants.

The results were then all consolidated and analyzed together. The correlations in Figure 19 demonstrate the overall correlations between all TAMCNs modeled. The TAMCN is a categorical variable applied to the different variants. Vehicle counts and TAMCN are negatively correlated because there are more vehicles in the D1001 than are in the D0187, by a factor of five.

Correlations							
	TAMCN	AM	VC	ProbCon	MPH	RC	RMSD
TAMCN	1.0000	-0.2924	-0.7144	-0.0005	-0.0002	-0.0001	0.1344
AM	-0.2924	1.0000	0.1965	0.0001	0.0017	0.0244	-0.0332
VC	-0.7144	0.1965	1.0000	0.0006	0.0029	0.0027	-0.4180
ProbCon	-0.0005	0.0001	0.0006	1.0000	-0.0087	0.0183	-0.0191
MPH	-0.0002	0.0017	0.0029	-0.0087	1.0000	-0.0206	0.0022
RC	-0.0001	0.0244	0.0027	0.0183	-0.0206	1.0000	0.0388
RMSD	0.1344	-0.0332	-0.4180	-0.0191	0.0022	0.0388	1.0000

Figure 19. Correlation coefficients for all variants together.

D1001, as can be seen in Table 4, has the smallest number of vehicles, yet the largest number of parts per vehicle in the model. With D1001, the RC factor and the

vehicle count have a larger impact on the overall RMSD. The importance of accessibility to accurate and thorough input data with modeling becomes more apparent given the impact that population and number of parts per platform have on the assessment of the model. These factors change with every MEF and for every TAMCN; thus, reusing an existing model is not as appealing as employing an automated model-building process.

Table 4. Design of experiments with the addition of the Parts Count column. The Parts Count is the number of parts modeled per vehicle.

Factors:		AM	VC	ProbCon	MPH	RC	Parts Count
D0187	low level	794	187	0.1	20	0.5	
	high level	2794	347	0.5	50	2	69
D1001	low level	802	49	0.1	20	0.5	
	high level	1802	93	0.5	50	2	174
D1002	low level	279	106	0.1	20	0.5	
	high level	2279	198	0.5	50	2	146

The apparent impact of parts to vehicle population ratio demonstrates a requirement to rethink how SOE DST displays output. Each legacy JLTV variant should contain more or less the same amount of parts. If SOE DST produced a by-part-number breakdown structure for a TAMCN, concern about the effects of parts density per vehicle in the model would be avoided. Additionally, a better understanding of all parts would be achieved.

#### D. FACTORS OF INTEREST BASED ON SENSITIVITY ANALYSIS

For initial sensitivity analysis, the scope was limited to D0187. Here the factors were regressed against the RMSD. Because of the NOLH DOE, true significant interactions are discovered.

For D0187 populations in all RACs, the DOE factors used accounted for 95% of the variability. The parameter estimates are shown in Figure 20. D0187 had the largest vehicle population and the lowest parts per vehicle modeled.

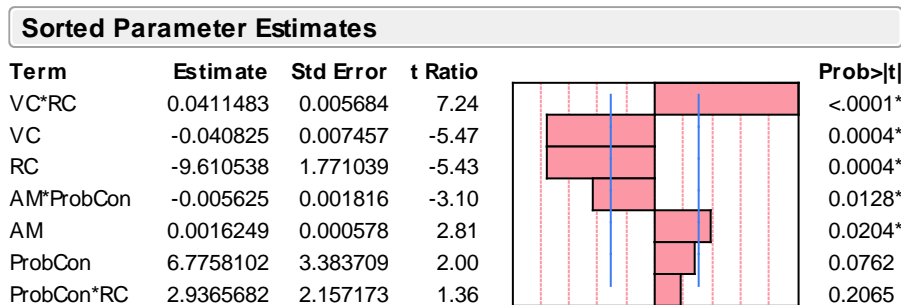


Figure 20. The parameter estimates for D0187 on 16 design points. The R-Squared for the model is 95%, with an adjusted of 92%. The model fits well.

D1001 models well, with an R-Squared of 0.75 and adjusted of 0.73. This indicates that there is a reasonable fit with the factors involved; however, the actual factors of interest are much different than those of D0187. For D1001, the interaction between RC and VC tends to be more significant than does RC alone, as seen in Figure 21. D1001's PartsUsage file has a small ratio of parts to vehicles. Specifically, for the low and high vehicle counts in the NOLH design, there are between 3.5 and 1.87 vehicles per part modeled.

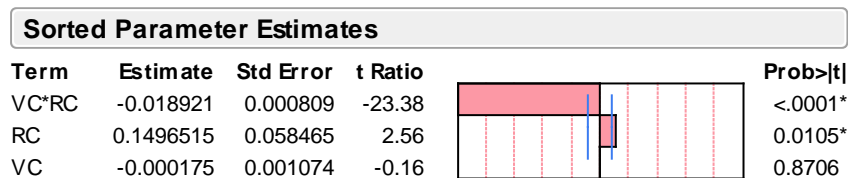


Figure 21. The parameter estimates for D0187 on 32 design points across 174 parts. The R-Squared for the model is 75% with and adjusted of 75%.

D1002 has a large vehicle population and a large number of parts per vehicle. The two combined to produce a lot of variability in the model. For D1002, there are between 1.38 and 0.73 vehicles per part in the models. The extreme points are associated with design points on the large end of the population and ratio change. In that situation, there are many vehicles, each with 146 parts and those parts are failing at a faster rate. This naturally will cause a large deviation from the real number of parts failures experienced by this population. The R-squared for the D1002 model is 0.22, with an adjusted 0.17. With this R-Squared, the model is not suited for use in “what if” analysis.

Given the extreme differences in the three models exposed to the DOE, there is little collected insight to be gained for the maintenance process alone. However, for all models, the ratio change and vehicle counts were main contributors to variability. While the R-squared values are considerably different between the models, there are great differences in the structure of the models. The difference in the models is a result of SOE DST data structure. A universal approach to the SOE DST data would provide continuity in TLMCM models in the future. Specifically, the following changes would help:

- Indenture structure for the TAMCN would ensure all its parts were reported.
- Work Unit Code or Logistics Control Number and Part Number in addition to NSN reporting will ensure parts failures are captured, rather than simply NSN failures.
- A complete list of parts associated with the TAMCN and its current failure rate will allow M&S to reflect all parts, not just those that failed during the reporting period drawn.
- The end item population used to compute failure rates in the SOE DST.

With these changes, a common picture of the TAMCNs could be achieved. Once done, DOE could lead to insights about factors affecting any number of measures of effectiveness. The purpose of this research was to develop the capability to conduct DOE analysis. Unfortunately, given the considerable differences between TAMCNs, possibly based on simple vehicle-to-parts ratios, the results are not able to be fully analyzed. While things may be said about individual TAMCNs, it is expected that a true picture of RMSD will not be possible without a complete (all parts modeled) model.



## **VII. INSIGHTS GAINED USEFUL TO FUTURE TLCM EFFORTS**

Many insights pertaining to the Marine Corps TLM process were gained from this research. Those insights have led to a realization that TLM models can be developed with the data that are currently being gathered in an automated manner. This automation of the process can lead to validation of the model-build process and put modeling in the hands of PMs to assist in policy decisions. Finally, conceptual future directions and opportunities to continue research were discovered.

### **A. VERIFICATION OF THE AUTOMATED-BUILD PROCESS**

This research originally was designed to explore a model created by Clockwork Solutions' contractors within the TLM-AT environment. While developing the background for the work, it was determined there is practicality in streamlining the model-build process in order to make maintenance modeling more accessible. This research built an automation tool that was proven capable of taking collected data and building adequate models. Prior to B-OLT, a rudimentary model built strictly from SOE DST and limited SME data took approximately three days by a trained TLM-AT user. The models can now be built, run, and output extracted in less than 10 minutes.

There are more steps that must be taken to build thorough models. Future work must be applied to discovering what data we should be collecting and how to automate data collection. Specifically, for TLM-AT models, there are modules that are not populated with B-OLT. By incorporating more data in SOE DST and expanding B-OLT a more thorough TLM-AT model may be built. A more complete model will allow for greater opportunities with modeling and simulation (M&S) in TLM.

### **B. ASSESSMENT OF B-OLT-GENERATED MODELS**

B-OLT drew data from SOE DST and verified that the models built in this automated fashion acted as they should. There was some variance from reality when back-assessing the models. These variances led to examination of the factors of interest of those variables captured in the model.

### **C. INITIAL FACTORS OF INTEREST IDENTIFIED USING SOE DST AND TLCM-AT**

Future work can lead to a better understanding of factors of interest in TLCM MOEs. B-OLT has made it possible to automatically build and extract data from TLCM-AT using data from SOE DST. SOE DST does not provide a complete vehicle structure to model in TLCM-AT. While TLCM-AT can be used with as many or as few parts as the user would like, quantitative analysis on TLCM effects requires some continuity between TAMCNs modeled. However, it is clear even from this research that the failure rate and vehicle counts are major contributors to RMSD.

### **D. SIGNIFICANCE OF AUTOMATED-BUILD PROCESS**

B-OLT provides TLCM professionals with an opportunity to systematically build models using the data synthesized by SOE DST. The automation allows the model-build process to be repeated—a critical step in model verification/validation efforts. Additionally, the B-OLT may be applied across TAMCNs.

#### **1. Time Involved in Manually Building TLCM-AT Models is Considerable**

Building a TLCM-AT model was at least a three-day process for a trained user prior to B-OLT. It is acknowledged that the models built *today* with B-OLT are not as robust as a three-day model-build using SMEs and multiple data sources; however, it is not far off. The reality is that this automated model-build technique may be refined and improved, and then applied across TAMCNs. It will take further exploration of SME factors, incorporation of TLCM requirements into the SOE DST, and analysis of models to determine what factors are important. Once determined, the next step must be exploring how we can automate the data-gathering step. No model will be better than the data it is built on and a commitment to TLCM demands a commitment to data collection.

#### **2. Opportunity for Use by All PMs for All TAMCNs**

PMs that are required to develop policy to improve mission availability, make projections of maintenance requirements, and ascertain the overall benefit of product

shifts (either PEI or component level) must be able to simulate the maintenance cycle. To do this, the model purchased by the Marine Corps must be accessible by the PM. It is acknowledged that simulations are not for the uninformed; however, a user-friendly model-build, coupled with TLCM-AT's ability to accept one or two variable changes, lends itself to quick, effective "what if" analysis. With that understanding, a uniform way of producing models with the data synthesized by SOE DST will provide model access to PMs.

### **3. Opportunity to Apply DOE to Policy Decisions**

The ability to quickly transfer data gathered into models with some level of assurance that they reflect reality leads to an opportunity to exercise that model to gain insight on potential policy decisions. Using a DOE, factors that affect, or do not affect, a MOE can be explored. B-OLT allows for quick and easy model-build and verification. Additionally, a loop was put around the code to accommodate NOLH DOE runs.

### **4. Opportunity to Work toward Model Validation**

Validation of a model requires control over the data used to build the model. By relying on SOE DST data, the models built using B-OLT can be reused and there is control over the data used to build the TLCM model. Validation can be accumulated through using the same process over several TAMCNs, time periods, and populations.

## **E. FUTURE WORK OPPORTUNITIES**

The work started with this thesis can be greatly expanded upon.

### **1. Exploration of Predictive Factors for TLCM-AT Airframe Models**

TLCM-AT was initially developed, and has been used, as a predictive model with airframes. Mechanical failures and the factors that affect these failures may be similar between air and ground equipment. An exploratory analysis of the predictive TLCM-AT airframe models built using a DOE may shed light onto factors that are important when predicting ground failures. Once this is determined, these factors of influence can be

gathered and modeled for ground equipment. If these factors turn out to be significant for ground equipment, further work will be in order.

## **2. Cost Benefit Analysis for Automating Data Collection**

Throughout the thesis process, gaps in data and hazy data were discovered. Given the importance of M&S, a cost benefit analysis of data collection automation is necessary. Specifically, benefits to effective models must be quantified. A cursory look will demonstrate that deployed units carry with them large quantities of spare parts that take up valuable embark space. If these parts are not used during the deployment, the cost of not having the capability to predict failures is the loss of embarkation space. This embarkation space, depending on the size, could be used for multiple PEIs, which could be useful in operational missions. Further, no matter which parts are carried on deployment, it seems there are always parts being shipped to the unit. Naturally, the cost of shipping translates to a cost associated to the unit's inability to anticipate requirements. Additionally, this causes down time for the PEI and an overall impact on the mission. If significant savings can be achieved through effective modeling and simulation, then data collection efforts must be improved.

## **3. Further Development of B-OLT Using Other Data Sources and Model Platforms**

Currently, B-OLT focuses on 12 of the 32 tables used in TLCM-AT. Further, B-OLT uses only one data source—SOE DST. B-OLT should be expanded to ensure all of TLCM-AT's functionality is taken advantage of in the future. Identification of elements missing in SOE DST is important, so they may be incorporated in future versions of SOE DST. It is reasonable to estimate that factors of importance identified in TLCM-AT models will be important in other TLCM models as well. As such, this identification and incorporation into SOE DST will serve the overall TLCM effort.

## **4. Application of the Model-Building Process to Promote its Validation of Maintenance Models**

B-OLT-built models must be constructed and scrutinized systematically to obtain a validated model within the TLCM community. This research limited its scope to five

legacy JLTV variants. Naturally, other Marine Corps assets must be evaluated using the B-OLT-build process. By gathering these histories, the TLCM community will gain confidence in the model-build process and application to insights aimed at assisting the decision-making process.

THIS PAGE INTENTIONALLY LEFT BLANK

## LIST OF REFERENCES

- Alionscience. (2005). Systems operational effectiveness decision support tool [Web site]. Retrieved March 2009 from <https://wstiac.alionscience.com/usmc>
- Catto, W. D. (2005). *Equipping the warfighter to win, strategic plan 2005~2009* [Powerpoint]. Retrieved February 2009 from <http://www.marcorsyscom.usmc.mil/aboutus/documents/Strategic+Plan+2005.pdf>
- Cioppa, T. M., & Lucas, T. W. (2007). Efficient nearly orthogonal and space-filling Latin hypercubes. *Technometrics*, 49, 45-55.
- Clockwork Solutions, Inc. (1992-2005). *Technical Reference Manual*. Aircraft Total Life Cycle Assessment Software Tool (ATLAST) Version 5.0. Austin, TX.
- Clockwork Solutions, Inc. (2007). Predictive modeling technology and consulting services in support of phase III TLCSM. Final Project Report (1992-2005). Submitted to Headquarters, Marine Corps Installations and Logistics.
- Devore, J. L. (2007). *Probability and statistics for engineering and the sciences* (7<sup>th</sup> ed.). Belmont, CA: Duxbury Press.
- Kelly, R. L. (2005). Subject: Marine Corps Life Cycle Management. Order 4000.57.
- Modeling and Simulation Coordination Office. (2006). *VV&A recommended practices guide*.
- TM 9-2320-387-24-2. (1997). *Army, 2, Technical Manual Body and Accessories*, Appendix B, Maintenance Allocation Chart.
- Winter, D. (2007). Subject: Department of the Navy Research and Development, Acquisition, Associated Life Cycle Management, and Logistics Responsibilities and Accountability. Instruction 5400.15C.
- Wolfowitz, P. (2004). Subject: Maintenance of Military Materiel. Directive Number 4151.18

THIS PAGE INTENTIONALLY LEFT BLANK



## INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center  
Ft. Belvoir, Virginia
2. Dudley Knox Library  
Naval Postgraduate School  
Monterey, California
3. Major Stephen H. Mount  
Marine Corps Systems Command  
Quantico, Virginia
4. Mike Tomlin  
Clockwork Solutions  
Austin, Texas
5. Mark Danison  
NAE & CNATT Requirements, N15  
Arlington, Virginia
6. Steven Nolan  
Logistics Operations Analysis Branch, I&L HQMC  
Washington, D.C.
7. Andrew Foote  
Alion Science and Technology Corporation  
Rome, New York
8. Robert Eberth  
JLTV M&S Sub-IPT  
Program Executive Office–Land Systems  
Quantico, Virginia
9. Director, Marine Corps Research Center  
MCCDC, Code C40RC  
Quantico, Virginia